SigmaXL® Version 4.21 Workbook

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SigmaXL® What's New in Version 4, Installation Notes, System Requirements and Getting Help

What's New in Version 4

New features in SigmaXL Version 4.21 include:

- Improved Histograms: X axis numeric labels now align with bin tick marks.

- Control Charts (**SigmaXL** > **Control Charts** > **"Tests for Special Causes" Defaults**):
    - Set defaults to apply any or all of Tests 1-8.
    - Test 2 can be set to 7, 8, or 9 points in a row on same side of CL.

- Change Time Format to Seconds (**SigmaXL** > **Data Manipulation** > **Data Preparation** > **Change Time Format to Seconds**) will calculate the number of seconds from time format. For example 0:00:00 converts to 0 seconds; 23:59:59 converts to 86399 seconds.

- Relocated "Clear Saved Defaults" Menu (**SigmaXL** > **Help** > **Clear Saved Defaults**). "Clear Saved Defaults" was previously in the Data Manipulation menu.

New features in SigmaXL Version 4.2 include:

- Normal Probability Plot (**SigmaXL** > **Graphical Tools** > **Normal Probability Plots**):
    - 95% Confidence Intervals to ease interpretation of normality/non-normality.

- Scatter Plots (**SigmaXL** > **Graphical Tools** > **Scatter Plots**):
    - Optional 95% Confidence Intervals added to Trendline. This provides a confidence interval for the mean of predicted $\hat{Y}$.
    - Optional 95% Prediction Intervals added to Trendline. This provides a confidence interval for the individual values of predicted $\hat{Y}$.

- Binary Logistic Regression (**SigmaXL** > **Statistical Tools** > **Regression** > **Binary Logistic Regression**):
    - Categorical (discrete) predictors can now be included in the model in addition to continuous predictors.
    - Wald Estimates (p-values) for categorical predictors.
    - Hosmer-Lemeshow goodness of fit test.
    - Measures of Association: Concordant/Discordant, Goodman-Kruskal Gamma, Somers' D and Kendall's Tau-a.

- Ordinal Logistic Regression (**SigmaXL** > **Statistical Tools** > **Regression** > **Ordinal Logistic Regression**):
    - Categorical (discrete) predictors can now be included in the model in addition to continuous predictors.
    - Wald Estimates (p-values) for categorical predictors.
    - Measures of Association: Concordant/Discordant, Goodman-Kruskal Gamma, Somers' D and Kendall's Tau-a.

New features in SigmaXL Version 4.1 include:

- Random Subset (**SigmaXL > Data Manipulation > Random Subset**):
    - Create a random subset of a worksheet with user specified number of rows.
    - Option to keep the subset in original order or randomly sort.
    - This feature is useful for data collection to ensure a random sample, e.g. given a list of transaction numbers select a random sample of 30 transactions.

- Box-Cox Power Transformation (**SigmaXL > Data Manipulation > Box-Cox Transformation** or **SigmaXL > Control Charts > Box-Cox Transformation**):
    - Apply automatic power transformations to data (Y^lambda, where lambda varies from -5 to +5).
    - This is used to convert non-normal data to normal.
    - Select rounded or optimal lambda to store transformed data. Rounded is typically preferred since it will result in a more "intuitive" transformation such as Ln(Y) or SQRT(Y).
    - Anderson-Darling normality test is applied to the transformed data so that you can immediately see whether or not the final transformation results in normal data.
    - Option to **not** store transformed data if Lambda=1 falls with the 95% confidence interval.
    - Option to **not** store the transformed data if it is not-normal, i.e. the resulting Anderson Darling Test p-value < .05.

- Gage R&R Study (**SigmaXL > Templates & Calculators > Gage R&R Study (MSA)**):
    - Added Variance Components and Percent Contribution to template report.

- Attribute Gage R&R (**SigmaXL > Templates & Calculators > Attribute Gage R&R (MSA)**) :
    - Added Cohen's Kappa to template report.

- Equal Variance Tests (**SigmaXL > Statistical tools > Equal Variance Tests**):
    - Bartlett's Test – multiple comparison of variances; used when all groups have normal data.
    - Levene's Test – multiple comparison of variances; used when one or more groups have non-normal data.
    - Welch's ANOVA – multiple comparison of means; equivalent to One-Way ANOVA, but used when the assumption of equal variances is not met.

- Binary Logistic Regression (**SigmaXL > Statistical Tools > Regression > Binary Logistic Regression**):
    - Powerful and user-friendly binary logistic regression.
    - Use when the response is binary (e.g. 0/1 or Pass/Fail).
    - Report includes a calculator to predict the response event probability for a given set of input X values.
    - Model summary and goodness of fit tests including Likelihood Ratio Chi-Square, Pseudo R-Square, Pearson Residuals Chi-Square, Deviance Residuals Chi-Square, Observed and Predicted Outcomes – Percent Correctly Predicted.

  - Stored data includes Event Probabilities, Predicted Outcome, Observed-Predicted, Pearson Residuals, Standardized Pearson Residuals, and Deviance Residuals.

- Ordinal Logistic Regression (**SigmaXL** > **Statistical Tools** > **Regression** > **Ordinal Logistic Regression**):
  - Powerful and user-friendly ordinal logistic regression.
  - Use when the response is ordinal (e.g. survey response 1,2,3,4,5).
  - Report includes a calculator to predict all response event probabilities for a given set of input X values.
  - Model summary and goodness of fit tests including Likelihood Ratio Chi-Square, Pseudo R-Square, Pearson Residuals Chi-Square, Deviance Residuals Chi-Square, Observed and Predicted Outcomes – Percent Correctly Predicted.
  - Stored data includes Event Probabilities and Predicted Outcome.

- Control Chart Advanced Limit Options (**SigmaXL** > **Control Charts, Advanced Limit Options**):
  - Calculate Control Limits with user specified subgroups.
  - Calculate Control Limits with historical groups. This results in split limits and is especially useful to demonstrate before improvement versus after improvement.

New features in SigmaXL Version 4.0 include:

- Recall SigmaXL Dialog
  - This will activate the last data worksheet and recall the last dialog, making it very easy to do repetitive analysis.
  - To access, click menu: **Recall SigmaXL Dialog** or Hot Key **F3** or **Alt-R**.
  - This can also be accessed by clicking **SigmaXL** > **Help** > **Hot Keys** > **Recall SigmaXL Dialog**.

- Activate Last Worksheet
  - This will activate the last data worksheet used without recalling the dialog.
  - To access, press hot key **F4**.
  - This can also be accessed by clicking **SigmaXL** > **Help** > **Hot Keys** > **Activate Last Sheet**.

- Normal Random Number Generator (**SigmaXL** > **Data Manipulation** > **Normal Random Data**) works with Recall SigmaXL Dialog (**F3**) to append columns to the current Normal Random Data worksheet. Column headings are automatically created with Mean and Standard Deviation values (e.g. 1: Mean = 0; Stdev = 1).

- Change Text Data Format to Numeric (**SigmaXL** > **Data Manipulation** > **Data Preparation** > **Change Text Data Format to Numeric**) will convert data that represents numeric values but is currently in text format. This sometimes occurs when importing data into Excel from another application or text file.

- Run Chart (**SigmaXL** > **Graphical Tools** > **Run Chart**) now includes a Nonparametric Runs Test. This allows you to test for Clustering, Mixtures, Lack of Randomness, Trends and Oscillation.

- One-Way ANOVA & Means Matrix (**SigmaXL > Statistical Tools > One-Way ANOVA & Means Matrix**) now includes an optional report for Sums-of-Squares (SS) details.

- Nonparametric Tests (**SigmaXL > Statistical Tools > Nonparametric Tests**):
  - 1 Sample Sign
  - 1 Sample Wilcoxon
  - 2 Sample Mann-Whitney
  - Kruskal-Wallis Median Test (includes graph of Group Medians and 95% Median Confidence Intervals)
  - Mood's Median Test (includes graph of Group Medians and 95% Median Confidence Intervals)
  - Runs Test (test for Clustering, Mixtures, Lack of Randomness, Trends and Oscillation).
- Power and Sample Size Calculators (**SigmaXL > Statistical Tools > Power & Sample Size Calculators**) for:
  - 1 Sample t-Test
  - 2 Sample t-Test
  - One-Way ANOVA
  - 1 Proportion Test
  - 2 Proportions Test

  The Power and Sample Size Calculators allow you to solve for Power (1 – Beta), Sample Size, or Difference (specify two, solve for the third). If used with Recall SigmaXL Dialog (**F3**) the results will be appended to the current worksheet. Excel graphs can then be generated to show the relationships between Power, Sample Size, and Difference.

- Power and Sample Size with Worksheets (**SigmaXL > Statistical Tools > Power & Sample with Worksheets**) for:
  - 1 Sample t-Test
  - 2 Sample t-Test
  - One-Way ANOVA
  - 1 Proportion Test
  - 2 Proportions Test

  The Power and Sample Size with Worksheets allows you to solve for Power (1 – Beta), Sample Size, or Difference (specify two, solve for the third). You must have a worksheet with Power, Sample Size, or Difference values along with other inputs such as Standard Deviation and Alpha. This is particularly useful to generate Excel graphs to show the relationships between Power, Sample Size, and Difference.

- Power and Sample Size Chart (**SigmaXL > Statistical Tools > Power & Sample Chart**) is used with the Power & Sample Size Calculator or Worksheet to quickly create a graph showing the relationship between Power, Sample Size and Difference.

Installation Notes

1. This installation procedure assumes that you have administrator rights to install software on your computer. Please uninstall any earlier (or trial) versions of SigmaXL.

2. If you are installing from a CD, the SigmaXL installer will run automatically. If you downloaded SigmaXL, please double-click on the file SigmaXL_Setup.exe.

3. We recommend that you accept all defaults during the install. Enter User Name, Company Name, and Serial Number. If this is a trial version, a serial number is not required for installation. If you purchased SigmaXL as a download, you received an order confirmation by e-mail. The order number is also your serial number. If you purchased a CD, the serial number is on the inside cover behind the CD. If you are unable to locate your serial number please call SigmaXL at 1-866-475-2124 (toll free in North America) or 1-416-236-5877.

4. Setup type should be “typical”. The installer will automatically create a desktop shortcut to SigmaXL.

5. To activate SigmaXL double-click on the SigmaXL desktop icon, or click Start > Programs > SigmaXL > SigmaXL.

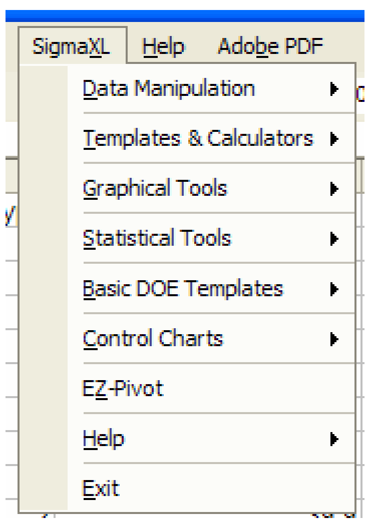
6. The following dialog box will appear on first use of SigmaXL:

7. Check “Always trust macros from this source” as shown below. SigmaXL is digitally signed by Verisign. Users can be confident that the code has not been altered or corrupted since it was created and signed.

8. Click "Enable Macros." Note that the prompt to enable macros will never be given again, unless SigmaXL is removed from the list of Trusted Sources. This list is available in Tools > Macro > Security. Click Trusted Sources.

9. An alternative approach to starting Excel add-ins, known as "demand load", starts the add-in automatically whenever Excel starts. This is NOT recommended due to potential software conflicts.

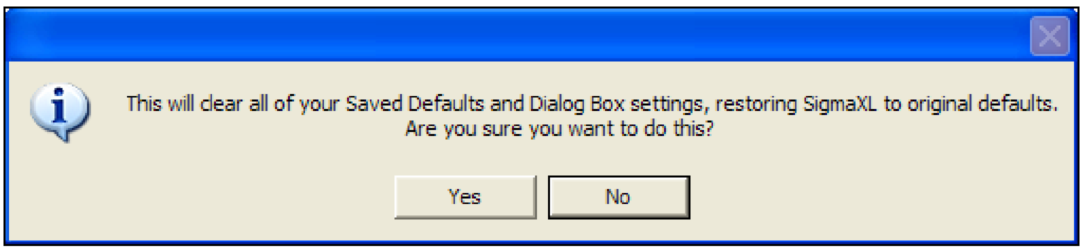
10. SigmaXL is added to Excel's menu system as shown:



Clear Saved Defaults

"Clear Saved Defaults" will reset all saved defaults such as Pareto and Multi-Vari Chart settings, saved control limits, and dialog box settings. All settings are restored to the original installation defaults.

Click SigmaXL > Help > Clear Saved Defaults. A warning message is given prior to clearing saved defaults.



SigmaXL® System Requirements

Minimum System Requirements:

Computer and processor: Personal computer with an Intel Pentium 233-MHz or faster processor (Pentium III recommended)

Memory: 256 megabytes (MB) of RAM or greater

Hard disk: 30 MB of available hard-disk space

Drive: CD-ROM or DVD drive

Display: Super VGA (800 × 600) or higher-resolution monitor

Operating system: Microsoft Windows® 2000 with Service Pack 3 (SP3), Windows XP, or later

Microsoft Excel version: Excel 2000 with Service Pack 3 (SP3), Excel XP, or Excel 2003.

Getting Help and Product Registration

To access the help system, please click SigmaXL > Help > Help.

Technical support is available by phone at 1-866-475-2124 (toll-free in North America) or 1-416-236-5877 or e-mail support@sigmaxl.com.

Please note that registered users obtain free technical support and upgrades for one year from date of purchase.

To register by web, simply click SigmaXL > Help > Register SigmaXL.

Introduction to SigmaXL®
Data Format and Tools Summary

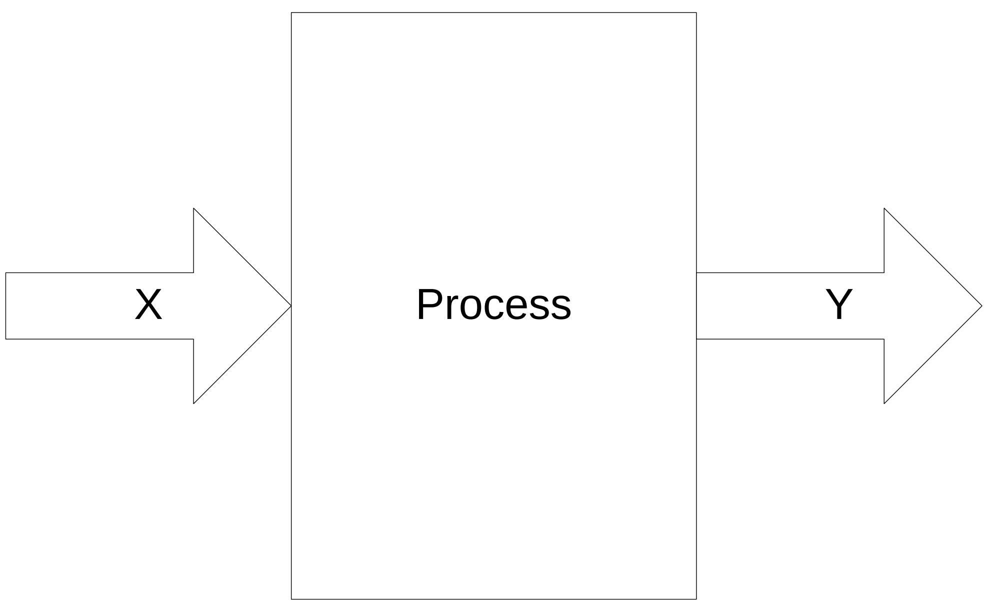
Introduction

SigmaXL 4.21 is a powerful but easy to use Excel Add-In that will enable you to Measure, Analyze, Improve and Control your service, transactional, and manufacturing processes. This is the perfect cost effective tool for Six Sigma Green Belts and Black Belts, Quality and Business Professionals, Engineers, and Managers.

SigmaXL will help you in your problem solving and process improvement efforts by enabling you to easily slice and dice your data, quickly separating the "vital few" factors from the "trivial many". This tool will also help you to identify and validate root causes and sources of variation, which then helps to ensure that you develop permanent corrective actions and/or improvements.

The Y=f(X) Model

SigmaXL utilizes the "Y=f(X)" model in its dialog boxes. Y denotes a key process output metric; X denotes a key process input metric. This process is shown pictorially as:



The mathematical expression Y = f(X) denotes that the variable Y is a function of X. Y represents the key process output metric(s), X denotes the key process input metric(s). Another way to view this is that Y is the effect of interest, and X is the cause. Examples of Y are Yield, Customer Satisfaction, and Order to Delivery Time. Examples of X are Raw Material Type, Responsiveness to Calls, and Location. The key is to figure out which X's from among many possible are the key X's and to what extent do they impact the Y's of interest. Solutions and improvements then focus on those key X's.

Data Types: Continuous Versus Discrete

X and Y metrics can each be continuous or discrete. A continuous measure will have readings on a continuous scale where a mid-point has meaning. For example, in a customer satisfaction survey using a 1 to 5 score, the value 3.5 has meaning. Other examples of continuous measures include cycle time, thickness, and weight. A discrete measure is categorical in nature. If we have Customer Types 1, 2, and 3, customer type 1.5 has no meaning. Other examples of discrete measures include defect counts and number of customer complaints.

It is possible to have various combinations of discrete/continuous X's and discrete/continuous Y's. Some examples are given below:

Examples of Discrete X and Discrete Y

- X = Customer Type, Y = Number of Complaints
- X = Product Type, Y = Number of Defects
- X = Day Shift vs. Night Shift, Y = Proportion of Defective Units

Examples of Discrete X and Continuous Y

- X = Customer Type, Y = Customer Satisfaction (1-5)
- X = Before Improvement vs. After Improvement, Y = Customer Satisfaction (1-5)
- X = Location, Y = Order to Delivery Time

Examples of Continuous X and Discrete Y

- X = Responsiveness to Calls (1-5), Y = Number of Complaints
- X = Process Temperature, Y = Number of Defects

Examples of Continuous X and Continuous Y

- X = Responsiveness to Calls (1-5), Y = Customer Satisfaction (1-5)
- X = Amount of Loan ($), Y = Cycle Time (Loan Application to Approval)

Note that in SigmaXL, a discrete X can be text or numeric, but a continuous X must be numeric. Y's must be numeric. If Y is discrete, count data will be required. If the data of interest is discrete text, it should be referenced as X1 and SigmaXL will automatically search through the text data to obtain a count (applicable for Pareto, Chi-Square and EZ-Pivot tools).

Stacked Data Column Format versus Unstacked Multiple Column Format

SigmaXL can accommodate two data formats: stacked column and unstacked multiple column. The stacked column format has an X column also referred to as the "Group Category" column and a Y column that contains the data of interest. The following is an example of data in stacked column format, with three unique groups of Customer Type:

Customer Type (X)	Overall Satisfaction (Y)
Type 2	3.5
Type 3	3.2
Type 3	3.3
Type 2	4.1
Type 1	3.2
Type 1	2.9
Type 1	1.9
Type 2	3.7
Type 3	4.0
Type 1	2.0
Type 3	2.6
Type 1	3.0
Type 2	4.1
Type 3	3.5
Type 2	5.0
Type 2	4.0
Type 3	4.4
Type 2	4.6
Type 1	2.5

If the data is in unstacked multiple column format, each unique group of X corresponds to a different column. The above data is now shown in unstacked format with customer satisfaction scores for each customer type in separate columns:

Sat_Type 1	Sat_Type 2	Sat_Type 3
3.2	3.5	3.2
2.9	4.1	3.3
1.9	3.7	4
2	4.1	2.6
3	5	3.5
2.5	4	4.4
	4.6	4.2

Summary of Graphical Tools

Tool	What	Type of Data	When to Use	Location in SigmaXL
Pareto Chart	Plots an ordered bar chart of the response	Y=Discrete X=Discrete	To separate the vital few from the trivial many, specify problem statement, and prioritize potential root causes.	SigmaXL > Graphical Tools > Basic Pareto Chart (Single) SigmaXL > Graphical Tools > Advanced Pareto Charts (Multiple)
Histogram	Visual display of one variable showing data center, spread, shape and outliers.	Y=Continuous	1. Summarize large amounts of data 2. To get a 'feel for the data' 3. To compare actual description to customer specs	SigmaXL > Graphical Tools > Basic Histogram (Single) SigmaXL > Graphical Tools > Histograms & Descriptive Statistics SigmaXL > Graphical Tools > Histograms & Process Capability
Box Plots	Visual display of the summary of Y data grouped by category of X.	Y=Continuous X=Discrete	Summary display to visualize differences in data center, spread and outliers across categories.	SigmaXL > Graphical Tools > Boxplots
Normal Probability Plot	Plots data in a straight line if the data is normally distributed.	Y=Continuous	To check for Normality and Outliers.	SigmaXL > Graphical Tools > Normal Probability Plots
Run Charts	Plots observations in time sequence	Y=Continuous or Discrete	To view process performance over time for trends, shifts or cycles. To test for Randomness using the Nonparametric Runs Test	SigmaXL > Graphical Tools > Run Charts
Multi-Vari Charts	Bar chart comparison of sub-groups on one variable.	Y=Continuous X=Discrete	To visually compare sub-groups by individual data points and the mean. To identify major sources of variation.	SigmaXL > Graphical Tools > Multi-Vari Charts
Scatter Plot (Diagram)	Plots a response Y versus a predictor X.	Y=Continuous X=Continuous	To understand the possible relationships between two variables. To identify possible root causes which are related to Y	SigmaXL > Graphical Tools > Scatter Plot SigmaXL > Graphical Tools > Scatter Plot Matrix
Control Charts	Plots observations in time sequence against a mean and control limits.	Y=Continuous or Discrete	To monitor the process over time for trends, shifts or cycles in order to control and improve process per-formance. To identify special causes.	SigmaXL > Control Charts >

Summary of Statistical Tools

Tool	What	Type of Data	When to Use	Location in SigmaXL
t-Test	Determine if there is a difference between two group means or if the mean of the data is equal to a standard value.	Y=Continuous X=Discrete	1. Test if mean = specified value 2. Test if 2 sample means are equal 3. Paired t: to reduce variation when comparing two sample means 4. Multiple pairwise comparisons	SigmaXL > Statistical Tools > 1 Sample t-Test & Confidence Intervals 2 Sample t-Test Paired t-Test One-Way ANOVA & Means Matrix
One-Way ANOVA (Analysis of Variance)	Determine if there is a difference in mean among many groups.	Y=Continuous X=Discrete	Determine of there is a statistically significant difference in means among the groups.	SigmaXL > Statistical Tools > One-Way ANOVA & Means Matrix
Nonparametric Tests	Determine if there is a difference between two or more group medians or if the median of the data is equal to a standard value.	Y=Continuous X=Discrete	1. Test if median = specified value: 1 Sample Sign Test or Wilcoxon 2. Test if 2 sample medians are equal: 2 Sample Mann-Whitney 3. Test if there is a difference in medians among the groups: Kruskal-Wallis or Mood's Median	SigmaXL > Statistical Tools > Nonparametric Tests
F-test / Bartlett's Test/ Levene's Test	Determine if there is a difference between two or more group variances.	Y=Continuous X=Discrete	1. Test if 2 sample variances (standard deviations) are equal. 2. Determine if there is a statistically significant difference for the variances among the groups. Use Bartlett's test for normal data. Use Levene's test for non-normal data.	SigmaXL > Statistical Tools > Two Sample Comparison Tests SigmaXL > Statistical Tools > Equal Variance Tests > Bartlett Levene
Proportions Test	Determine if there is a difference between two proportions or if the proportion of the data is equal to a standard value.	Y=Discrete X=Discrete	1. Test if sample proportion = specified value 2. Determine of there is a statistically significant difference for two proportions.	SigmaXL > Calculators > 1 Proportion Confidence Interval 2 Proportions Test
X^2 Chi Square	Determine if there is a difference for observed frequencies of 2 discrete variables.	Y=Discrete X=Discrete	Determine if there is a relationship between two discrete variables.	SigmaXL > Statistical Tools > Chi-Square Chi-Square - Two-Way Table Data
Anderson-Darling Normality Test	Determine if the data is normally distributed.	Y=Continuous	Test if the sample data is normally distributed.	SigmaXL > Graphical Tools > Histograms & Descriptive Statistics SigmaXL > Statistical Tools > Descriptive Statistics
Correlation	Quantify strength of relationships.	Y=Continuous X=Continuous	Determine if there is evidence of a relationship between Xs and Ys, quantify the relationship, identify root causes.	SigmaXL > Statistical Tools > Correlation Matrix
Regression (Simple Linear & Multiple)	Summarizes, describes, predicts and quantifies relationships.	Y=Continuous X=Continuous	1. Determine if there is evidence of a relationship between Xs and Ys. 2. Model data to develop a mathematical equation to quantify the relationship. 3. Identify root causes. 4. Make predictions using the model.	SigmaXL > Statistical Tools > Regression > Multiple Regression
Logistic Regression	Summarizes, describes, predicts and quantifies relationships.	Y=Discrete (Binary or Ordinal) X=Continuous	1. Determine if there is evidence of a relationship between Xs and Ys. 2. Model data to develop a mathematical equation to quantify the relationship. 3. Identify root causes. 4. Make predictions using the model.	SigmaXL > Statistical Tools > Regression > Binary Logistic Regression Ordinal Logistic Regression
Design of Experiments (DOE)	Systematic and efficient proactive approach to testing relationships.	Y=Continuous or Discrete X=Continuous or Discrete	To establish cause and effect relationship between Ys and Xs. To identify 'vital few' Xs.	SigmaXL > Basic DOE Templates

SigmaXL: Measure Phase Tools

Part A - Basic Data Manipulation

Introduction to Basic Data Manipulation

Open **Customer Data.xls**. This data is in "stacked" column format. This format is highly recommended for use with SigmaXL. Note that all pertinent information is provided in each record (row). Also note that only one row is used for column headings (labels) and there are no blank rows or columns. Each column contains a consistent format of either numeric, text, or date. This is also the data format used by other Statistical software packages such as Minitab and JMP.

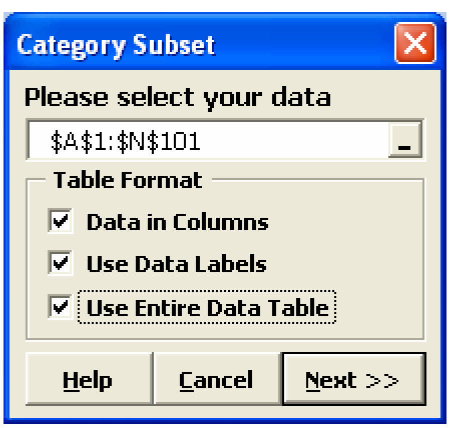
Customer Record No	Order Date	Customer Type	Avg No. of orders per mo	Avg days Order to delivery time	Loyalty - Likely to Recommend	Overall Satisfaction	Responsive to Calls	Ease of Communications	Staff Knowledge	Size of Customer	Major-Complaint	Product Type
1	1/5/2001	2	24	38	4	3.54	3.02	4.07	1.65	Small	Return-calls	Consumer
2	1/5/2001	3	36.4	42	4	3.16	3.21	3.11	3.8	Large	Difficult-to-order	Consumer
3	1/5/2001	2	32.8	44	2	2.42	1.93	2.9	2.88	Small	Return-calls	Manufacturer
4	1/5/2001	2	47.6	48	3	2.7	1.88	2.52	4.08	Large	Difficult-to-order	Manufacturer
5	1/5/2001	3	30.6	51	3	3.31	3.75	2.86	3.88	Small	Not-available	Consumer
6	1/5/2001	2	52.2	55	4	4.12	4.31	3.93	1.12	Large	Return-calls	Consumer
7	1/5/2001	1	35.8	49	4	3.24	4.06	2.42	4.64	Large	Return-calls	Manufacturer
8	1/5/2001	2	36.5	39	4	4.47	4.75	4.2	4.98	Large	Return-calls	Manufacturer
9	1/5/2001	2	39.9	44	4	3.83	3.18	4.48	3.16	Large	Difficult-to-order	Consumer
10	1/5/2001	1	28	43	3	2.94	2.03	3.85	4.01	Small	Return-calls	Consumer
11	1/8/2001	2	25.9	44	3	3.24	3.05	4.43	4.72	Small	Return-calls	Manufacturer
12	1/8/2001	2	23.9	50	3	4.18	3.67	4.69	4.86	Small	Difficult-to-order	Manufacturer
13	1/8/2001	2	37.9	58	5	4.53	4.29	4.77	1.9	Large	Return-calls	Consumer

Note that Loyalty, Overall Satisfaction, Responsive to Calls, Ease of Communications, and Staff Knowledge were obtained from surveys. A Likert scale of 1 to 5 was used, with 1 being very dissatisfied, and 5 very satisfied. Survey results were averaged to obtain non-integer results.

Category Subset

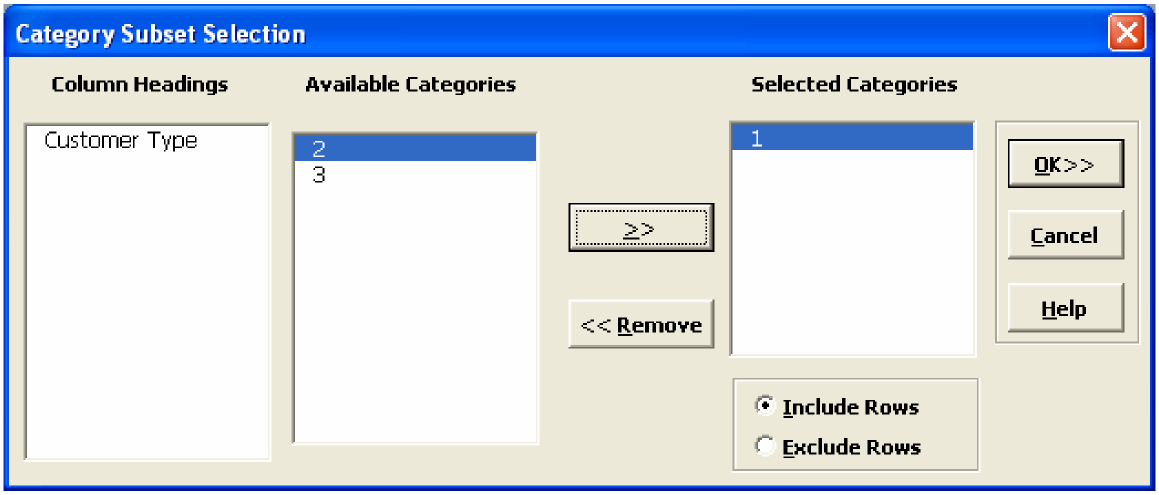
1. Click SigmaXL > Data Manipulation > Category Subset

2. If you are working with a portion of a dataset, specify the appropriate range, otherwise check "Use Entire Data Table"



3. Check "Use Entire Data Table". Click Next.

4. Select Customer Type, 1, >> as shown:



5. Click OK

A new subset worksheet is created containing only Customer Type 1.
Note: We could have chosen more than one Customer Type and had the option to create a subset which included or excluded these Customer Types.

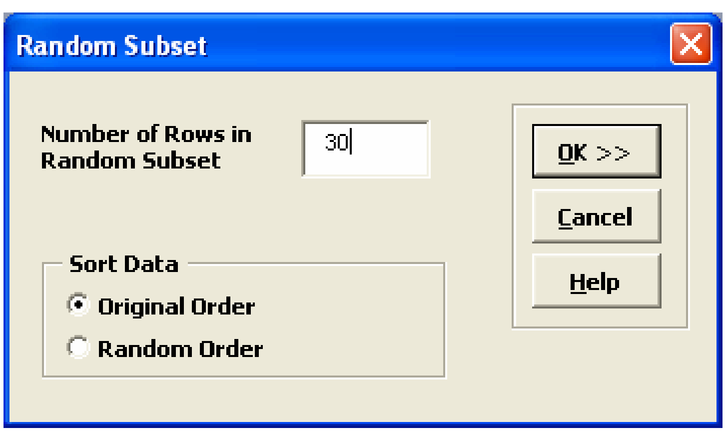
Random Subset

1. Click Sheet 1 Tab of **Customer Data.xls**

2. Click SigmaXL > Data Manipulation > Random Subset.

3. Ensure that the entire data table is selected. If not, check "Use Entire Data Table". Click Next.

4. Enter "Number of Rows in Random Subset" as 30. The default Sort selection is Original Order.



5. Click OK. A new worksheet is created that contains a random subset of 30 rows. This feature is useful for data collection to ensure a random sample, e.g. given a list of transaction numbers select a random sample of 30 transactions.

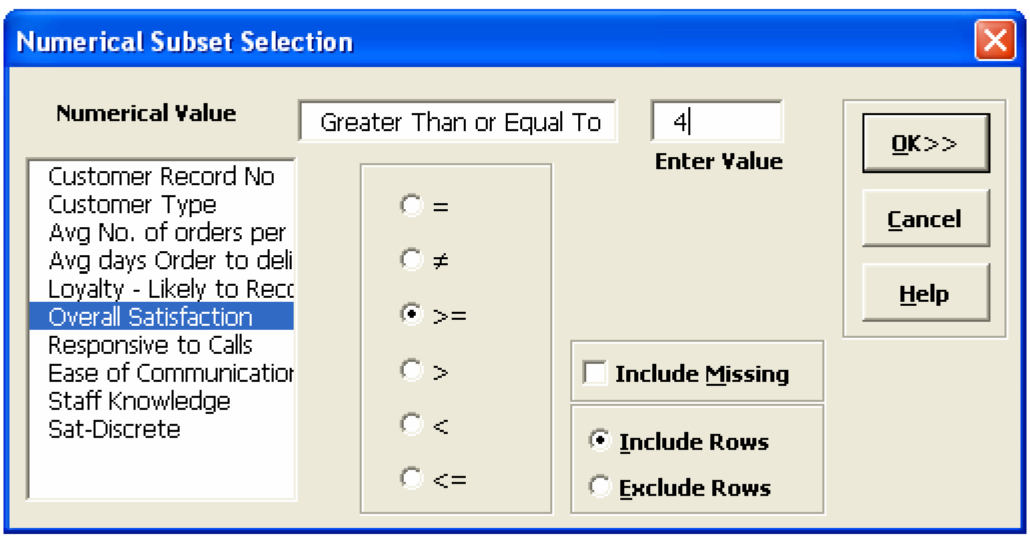
Numerical Subset

1. Click Sheet 1 Tab of **Customer Data.xls**

2. Click SigmaXL > Data Manipulation > Numerical Subset

3. Ensure that entire data table is selected. If not, check “Use Entire Data Table”. Click Next.

4. Select Overall Satisfaction, >=, Enter Value “4”



5. Click OK
   A new subset worksheet is created containing only those rows with Overall Satisfaction >= 4.

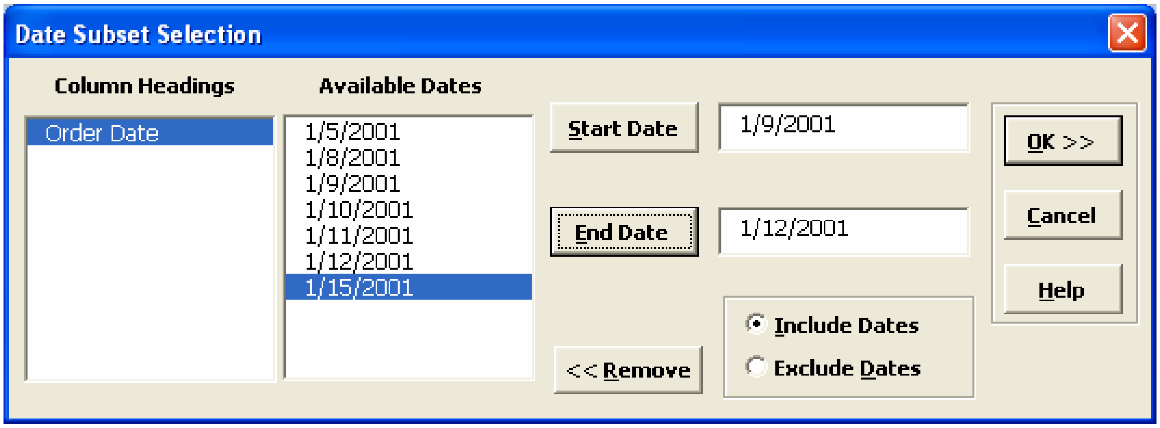
Date Subset

1. Click Sheet 1 Tab of **Customer Data.xls**

2. Click SigmaXL > Data Manipulation > Date Subset

3. Ensure that entire data table is selected. If not, check “Use Entire Data Table”. Click Next.

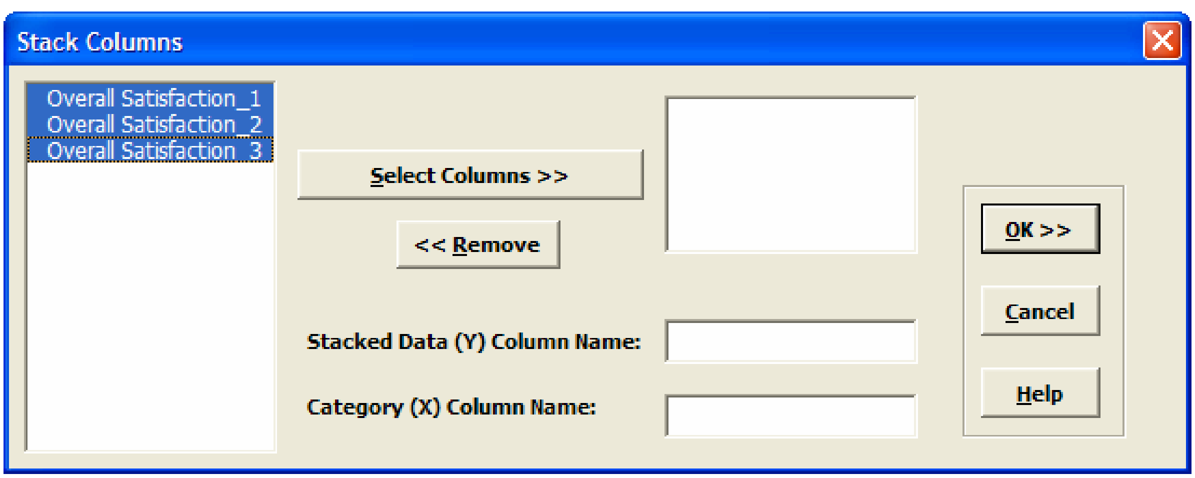
4. Select Order Date, select 1/8/2001, click Start Date, select 1/12/2001, click End Date



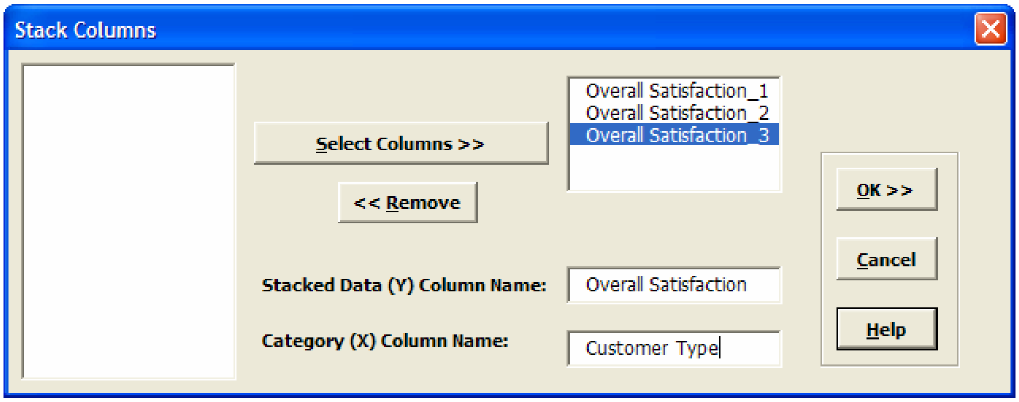
5. Click OK
   A new subset worksheet is created containing only those rows with Order Date between 1/9/2001 to 1/12/2001.

Stack Columns

1. Open **Customer Satisfaction Unstacked.xls**
2. Click SigmaXL > Data Manipulation > Stack Columns
3. Check "Use Entire Data Table", click Next
4. Shift Click on Overall Satisfaction_3 to highlight all three column names as shown:



5. Select the Columns (>>). Enter the Stacked Data (Y) Column Name as "Overall Satisfaction". Enter the Category (X) Column Name as "Customer Type".



6. Note that a selected column may be removed by highlighting and double-clicking or clicking the Remove button.

7. Click OK. Shown is the resulting stacked column format:

Customer Type	Overall Satisfaction
Overall Satisfaction_1	3.24
Overall Satisfaction_1	2.94
Overall Satisfaction_1	1.86
Overall Satisfaction_1	2.04
Overall Satisfaction_1	2.96
Overall Satisfaction_1	2.53
Overall Satisfaction_1	4.67
Overall Satisfaction_1	4.67
Overall Satisfaction_1	2.57
Overall Satisfaction_1	3.09
Overall Satisfaction_1	3.57
Overall Satisfaction_1	4.25
Overall Satisfaction_1	4.05
Overall Satisfaction_1	3.58
Overall Satisfaction_1	3.82
Overall Satisfaction_1	3.8
Overall Satisfaction_1	2.81
Overall Satisfaction_1	3.99
Overall Satisfaction_1	4.15
Overall Satisfaction_1	3.56
Overall Satisfaction_1	3.26
Overall Satisfaction_1	4.8
Overall Satisfaction_1	1.72
Overall Satisfaction_1	3.01
Overall Satisfaction_1	2.65
Overall Satisfaction_1	3.92
Overall Satisfaction_1	4.24
Overall Satisfaction_1	3.97
Overall Satisfaction_1	4.02
Overall Satisfaction_1	2.56
Overall Satisfaction_1	2.9
Overall Satisfaction_2	3.54
Overall Satisfaction_2	2.42
Overall Satisfaction_2	2.7

8. Data that is in stacked column format can be unstacked using Data Manipulation > Unstack Column.

Normal Random Data

The normal random data generator is used to produce normal random data. Column headings are automatically created with Mean and Standard Deviation values (e.g. 1: Mean = 0; Stdev = 1). This utility works with Recall SigmaXL Dialog (**F3**) to append columns to the current Normal Random

Data worksheet. An example is shown in **Measure Phase Tools, Part F – Normal Probability Plots**.

Box-Cox Transformation

This tool is used to convert non-normal data to normal by applying a power transformation. Examples of use are given in **Measure Phase Tools, Part H – Process Capability for Non-Normal Data** and **Control Phase Tools, Part A – Individuals Charts for Non-Normal Data**.

Data Preparation – Remove Blank Rows and Columns

This data preparation utility is provided as a convenient way to prepare data for analysis by deleting any empty rows and/or columns.

1. Open **Customer Data.xls.** Click Sheet 1 Tab.

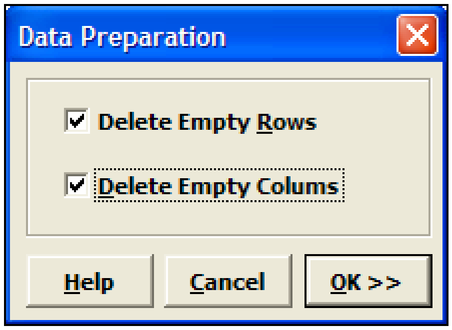
2. Insert a new column in B; Click column B heading, click Insert > Columns.

3. Insert a new row in row 2. Click row 2 label, click Insert > Rows as shown:

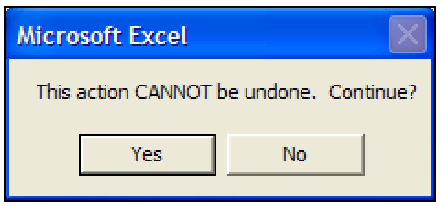
	A	B	C	D
1	Customer Record No		Order Date	Customer Type
2				
3	1		1/5/2001	2
4	2		1/5/2001	3
5	3		1/5/2001	2
6	4		1/5/2001	2
7	5		1/5/2001	3
8	6		1/5/2001	2
9	7		1/5/2001	1
10	8		1/5/2001	2
11	9		1/5/2001	2
12	10		1/5/2001	1

4. This is now an example of a data set that requires deletion of empty rows and columns. Click SigmaXL > Data Manipulation > Data Preparation > Remove Blank Rows and Columns.

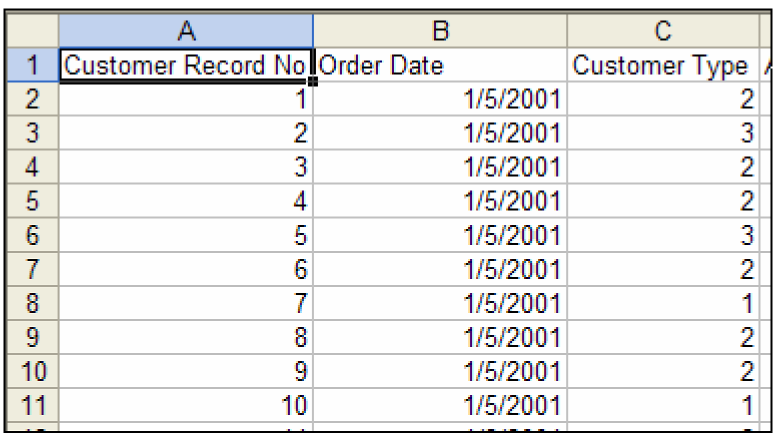
5. Check Delete Empty Rows and Delete Empty Columns.



6. Click OK. A warning message is given prior to the deletion step.



7. Click Yes. The empty rows and columns are deleted automatically.



	A	B	C
1	Customer Record No	Order Date	Customer Type
2	1	1/5/2001	2
3	2	1/5/2001	3
4	3	1/5/2001	2
5	4	1/5/2001	2
6	5	1/5/2001	3
7	6	1/5/2001	2
8	7	1/5/2001	1
9	8	1/5/2001	2
10	9	1/5/2001	2
11	10	1/5/2001	1

Data Preparation – Change Text Data Format to Numeric

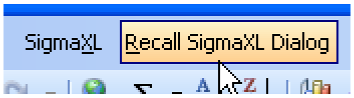
This data preparation utility will convert data that represents numeric values but is currently in text format. This sometimes occurs when importing data into Excel from another application or text file.

Data Preparation – Change Time Format to Seconds

Change Time Format to Seconds will calculate the number of seconds from time format. For example 0:00:00 converts to 0 seconds; 23:59:59 converts to 86399 seconds.

Recall SigmaXL Dialog

Recall SigmaXL Dialog is used to activate the last data worksheet and recall the last dialog, making it very easy to do repetitive analysis. To access, click the top level menu "Recall SigmaXL Dialog" located to the right of the SigmaXL menu:



Alternatively you can use the Hot Key **F3** or **Alt-R**. This feature can also be accessed by clicking SigmaXL > Help > Hot Keys > Recall SigmaXL Dialog.

Activate Last Worksheet

Activate Last Worksheet is used to activate the last data worksheet without recalling the dialog. To access, press hot key **F4**. This feature can also be accessed by clicking SigmaXL > Help > Hot Keys > Activate Last Sheet.

Part B – Templates & Calculators

Introduction to Templates & Calculators

All SigmaXL generated templates and calculators (except Gage R&R and DOE) are stand alone worksheets; they do not require that SigmaXL be active to be used. Simply enter the inputs and resulting outputs are produced immediately. If the template does not automatically perform the calculations, click Tools > Options, select Calculation, Automatic, and click OK. Templates and Calculators are protected worksheets by default, but this may be modified by clicking Tools > Protection > Unprotect Sheet. Gage R&R is password protected, so it cannot be unprotected. Click SigmaXL > Templates & Calculators to access these templates and calculators:

- Cause & Effect (XY) Matrix
- Failure Mode & Effects Analysis (FMEA)
- Sample Size – Discrete
- Sample Size – Continuous
- Gage R&R Study (MSA)
- Gage R&R: Multi-Vari & X-bar R Charts
- Attribute Gage R&R (MSA)
- Process Sigma – Discrete
- Process Sigma – Continuous
- Process Capability
- Process Capability & Confidence Intervals
- Standard Deviation Confidence Interval
- 1 Proportion Confidence Interval
- 2 Proportions Test

Cause & Effect (XY) Matrix – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **C&E Matrix**. This is a simple Cause and Effect Matrix example for a Call Center.

CAUSE & EFFECT (XY) MATRIX

Process/Project Name:	Call Center Example
Date:	
Performed By:	
Notes:	

Output Variables (Y's):	Call Abandon Rate	Customer Satisfaction	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	
Importance Score (1-10):	8	10									
Input/Process Variables (X's)	Table of Association Scores (X's to Y's)										Weighted Score
Answer Speed	9	9									162
Employee Experience	1	3									38
First Time Resolution	0	9									90
X4											0

Notes for use of the Cause and Effect Matrix template, also known as the XY Matrix:

1. Weight the Output Variables (Y's) on a scale of 1 to 10 with 10 indicating most important to the Customer.

2. For Root Cause Analysis, assign the association/effect multiplier score for each X to Y using a scale of 0, 1, 3, 9, where 0 = None, 1 = Weak, 3 = Moderate, and 9 = Strong. Initially this assignment will likely be a team subjective assessment. Data should be collected and the degree of association should be validated with Graphical and Statistical Tools.

3. For Project Selection or Solution Selection, assign the association multiplier score for each X to Y using a scale of 1 to 10, with 10 indicating strong association.

Failure Mode & Effects Analysis (FMEA) – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **FMEA**. This is a simple Failure Mode and Effects example for Stocking Inventory.

Potential Failure Mode & Effects Analysis

Process/Product:	Stock Inventory
FMEA Team:	
Responsibility:	
Prepared By:	

Process								
Process Steps or Product Functions	Potential Failure Mode	Potential Effects of Failure	Severity (1-10)	Potential Cause(s) of Failure	Occurrence (1-10)	Current Controls	Detection (1-10)	Risk Priority Number (RPN)
Stock inventory	Stock in wrong location	Unable to locate stock	5	Correct location is full	7	Stock checked twice a year	9	315
Stock inventory	Damaged	Insufficient product	7	Supplier Defect	3	Incoming Inspection	8	168
Stock inventory	Damaged	Insufficient product	7	Handling Error	5	Standard Operating Procedures	9	315

Recommended scales for Severity, Occurrence, and Detection are shown below:

Score	Severity Guidelines	
	AIAG	Six Sigma
10	Hazardous without warning	Injure a customer or employee
9	Hazardous with warning	Be illegal
8	Very High	Render product or service unfit for use
7	High	Cause extreme customer dissatisfaction
6	Moderate	Result in partial malfunction
5	Low	Cause a loss of performance which is likely to result in a complaint
4	Very Low	Cause minor performance loss
3	Minor	Cause a minor nuisance but can be overcome with no performance loss
2	Very Minor	Be unnoticed and have only minor effect on performance
1	None	Be unnoticed and not affect the performance

Bad ↓ Good

Score	Occurrence Guidelines		
	AIAG	Six Sigma	
10	Very High: Persistent Failures, Ppk < 0.55	More than once per day	> 30%
9	Very High: Persistent Failures, Ppk >= 0.55	Once every 3-4 days	< 30%
8	High: Frequent Failures, Ppk >= 0.78	Once every week	< 5%
7	High: Frequent Failures, Ppk >= 0.86	Once per month	< 1%
6	Moderate: Occasional Failures, Ppk >= 0.94	Once every 3 months	< 0.03%
5	Moderate: Occasional Failures, Ppk >= 1.00	Once every 6 months	< 1 per 10,000
4	Moderate: Occasional Failures, Ppk >= 1.10	Once per year	< 6 per 100,000
3	Low: Relatively Few Failures, Ppk >=1.20	Once every 1-3 years	< 6 per million
2	Low: Relatively Few Failures, Ppk >=1.30	Once every 3-6 years	< 3 per 10 million
1	Remote: Failure is Unlikely, Ppk >=1.67	Once every 6-9 years	< 2 per billion

Bad ↓ Good

Score	Detection Guidelines	
	AIAG	Six Sigma
10	Almost Impossible: Absolute certainty of non-detection	Defect caused by failure is not detectable
9	Very Remote: Controls will probably not detect	Occasional units are checked for defects
8	Remote: Controls have poor chance of detection	Units are systematically sampled and inspected
7	Very Low: Controls have poor chance of detection	All units are manually inspected
6	Low: Controls may detect	Manual inspection with mistake-proofing modifications
5	Moderate: Controls may detect	Process is monitored (SPC) and manually inspected
4	Moderately High: Controls have a good chance to detect	SPC is used with an immediate reaction to out of control conditions
3	High: Controls have a good chance to detect	SPC is above 100% inspection surrounding out of control conditions
2	Very High: Controls almost certain to detect	All units are automatically inspected
1	Very High: Controls certain to detect	Defect is obvious and can be kept from affecting the customer

Bad ↓ Good

Sample Size – Discrete Calculator Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Sample Size Discrete**.

Sample Size Calculator - Discrete Data		
Estimate of Proportion:	P	0.5
Desired margin of error:	delta	0.03
Population Size (optional):	N	
Minimum Sample Size:	n	1068
	n (adjusted for small N)	
	np check (should be >= 5)	534

Notes for use of the Sample Size – Discrete Calculator:

1. P is estimate of proportion for outcome of interest. Use P = 0.5 if unknown.
2. Delta is desired proportion margin of error. Enter as the half-width, i.e. if the desired margin of error is +/- 3%, enter 0.03.
3. The margin of error is a 95% confidence interval.
4. Enter population size N to adjust for small populations (N < 10000).
5. np should be >= 5. If necessary, reduce delta to adjust.

Sample Size – Continuous Calculator Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Sample Size Continuous**.

Sample Size Calculator - Continuous Data		
Estimate of Standard Deviation:	s	1
Desired margin of error:	delta	0.25
Population Size (optional):	N	
Minimum Sample Size:	n	62
	n (adjusted for small N)	

Notes for use of the Sample Size – Continuous Calculator:

1. Delta uses the same units as the standard deviation. Enter as the half-width, i.e., if the desired margin of error is +/- 0.25, enter 0.25.

2. The margin of error is a 95% confidence interval.

3. Enter (optional) population size N to adjust for small populations (N < 1000).

Gage R&R Study (MSA) – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Gage R&R**.

Gage Name:	Example Data
Date of Study:	
Performed By:	
Notes:	

Process Tolerance	
USL:	2
LSL:	1

StDev Multiplier:	6

Operator A	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Reading 1	1.34	1.31	1.52	1.44	1.44	1.29	1.52	1.49	1.44	1.52
Reading 2	1.31	1.36	1.52	1.42	1.49	1.23	1.52	1.49	1.47	1.52
Reading 3										

Operator B	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Reading 1	1.29	1.29	1.55	1.42	1.42	1.21	1.52	1.49	1.39	1.52
Reading 2	1.29	1.26	1.49	1.39	1.39	1.21	1.55	1.47	1.36	1.49
Reading 3										

Operator C	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Reading 1	1.26	1.44	1.55	1.42	1.42	1.23	1.52	1.49	1.42	1.55
Reading 2	1.29	1.42	1.52	1.42	1.42	1.26	1.55	1.49	1.42	1.55
Reading 3										

Gage R&R Metrics	Variance Component	% Contribution of Variance Component	StDev	StDev * Multiplier	% Total Variation (TV)	% Tolerance
Gage R&R:	0.001289167	11.44	0.035904967	0.215429803	33.83	21.54
Operator (AV Appraiser Variation):	0.000258426	2.29	0.016075631	0.096453789	15.15	9.65
Operator * Part (INT Interaction):	0.000627407	5.57	0.025048102	0.150288611	23.60	15.03
Reproducibility (SQRT(AV^2 + INT^2)):	0.000885833	7.86	0.029762952	0.178577714	28.04	17.86
Repeatability (EV Equipment Variation):	0.000403333	3.58	0.02008316	0.120498963	18.92	12.05
Part Variation (PV):	0.009977222	88.56	0.099886046	0.599316277	94.10	59.93
Total Variation (TV):	0.011266389	100.00	0.106143247	0.636859482	100.00	63.69

Notes for use of the Gage R&R Template:

1. Recommended study includes 10 Parts, 3 Operators and 3 Repeats. The template calculations will work with a minimum of 2 Operators, 2 Parts and 2 Repeats. The data should be balanced with each operator measuring the same number of parts and the same number of repeats.

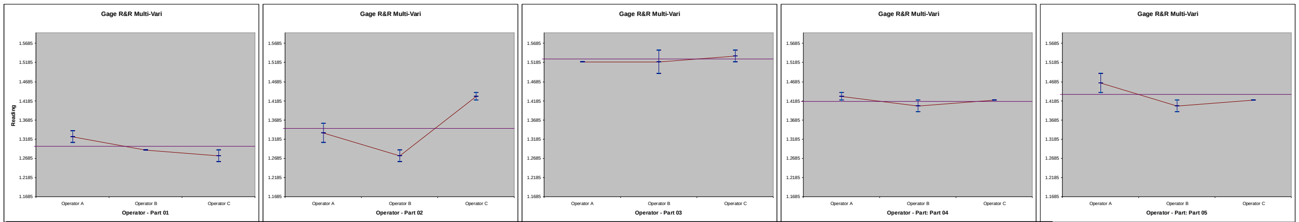
2. Enter process Upper Specification Limit (USL) and Lower Specification Limit (LSL) in the Process Tolerance window. This is used to determine the % Tolerance metrics. If the specification is single-sided, leave both entries blank.

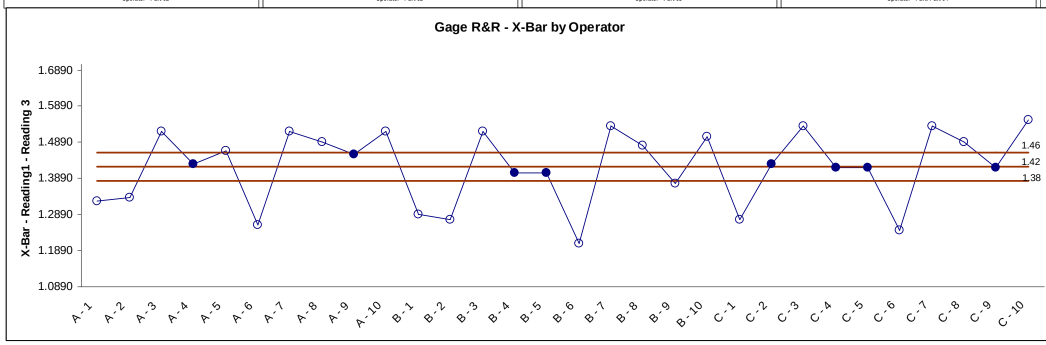
3. The default StDev multiplier is 6. Change this to 5.15 if AIAG convention is being used.

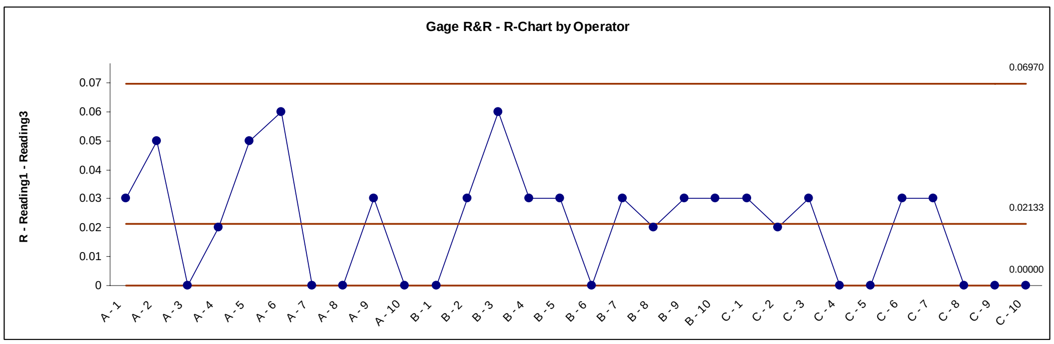
4. The cells shaded in light blue highlight the critical metrics Gage R&R % Total Variation (also known as %R&R) and %Tolerance. (< 10% = Good Measurement System; > 30% = Bad Measurement System).

Gage R&R: Multi-Vari & X-bar R Charts – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheets named **Gage R&R - Multi-Vari** and **Gage R&R – X-Bar R.**







Notes for use of the Gage R&R: Multi-Vari & X-bar R Charts:

1. The Gage R&R Multi-Vari and X-bar & R charts can only be generated if a Gage R&R template has been completed and is the active worksheet. Select the Gage R&R worksheet and click **SigmaXL > Templates & Calculators > Gage R&R: Multi-Vari & X-Bar R Charts** to create the above charts.

2. The Multi-Vari chart shows each Part as a separate graph. Each Operator's response readings are denoted as a vertical line with the top tick corresponding to the Maximum value, bottom tick is the Minimum, and the middle tick is the Mean. The horizontal line across each graph is the overall average for each part.

3. When interpreting the X-bar and R chart for a Gage R&R study, it is desirable that the X-bar chart be out-of-control, and the Range chart be in-control. The control limits are derived from within Operator repeatability.

Attribute Gage R&R (MSA) – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Attribute MSA.**

MEASUREMENT SYSTEM STUDY FOR ATTRIBUTE DATA (Recommend 3 Appraisers, 2 Repeats, Minimum of 10 Good Parts and 10 Bad Parts)

Product/Unit Name:	Example Attribute MSA
Date of Study:	
Performed By:	
Notes:	

Good Part or Unit:	G
Bad Part or Unit:	NG

Part	True Standard	Appraiser A Trial # 1	Appraiser A Trial #2	Appraiser B Trial # 1	Appraiser B Trial #2	Appraiser C Trial # 1	Appraiser C Trial #2
1	G	G	G	NG	G	G	G
2	G	NG	G	G	G	G	G
3	NG	NG	NG	NG	NG	NG	NG
4	G	G	G	G	NG	G	G
5	NG	NG	NG	NG	NG	NG	NG
6	NG	NG	NG	NG	NG	NG	NG
7	G	G	G	NG	G	G	G
8	NG	NG	NG	NG	NG	NG	NG
9	G	G	G	G	G	G	G
10	NG	NG	NG	NG	NG	NG	NG
11	G	G	G	NG	G	G	G
12	NG	NG	NG	NG	NG	NG	NG
13	NG	NG	NG	NG	NG	NG	NG
14	G	NG	G	NG	G	G	G
15	NG	NG	NG	NG	G	NG	NG
16	G	G	NG	G	G	G	NG
17	G	G	G	G	G	G	G
18	NG	NG	NG	NG	G	NG	NG
19	NG	NG	NG	NG	NG	NG	NG
20	G	G	G	NG	G	G	G

Attribute MSA Analysis:

Within Appraiser Agreement:	# Inspected	# Matched	Percent	95% LC	95% UC	Cohen's Kappa
A	20	17	85.00%	62.11%	96.79%	0.6939
B	20	12	60.00%	36.05%	80.88%	0.2381
C	20	19	95.00%	75.13%	99.87%	0.9000

Type I = False Reject (Appraiser Rejected Good Part)
Type II = False Accept (Appraiser Accepted Bad Part)
Mixed = Assessments across trials are not identical

Each Appraiser vs Standard Agreement:	# Inspected	# Matched	Percent	95% LC	95% UC	Type I Errors	Type I Error %	Type II Errors	Type II Error %	Mixed Error	Mixed Error %	Cohen's Kappa
A	20	17	85.00%	62.11%	96.79%	0	0.00%	0	0.00%	3	15.00%	0.8500
B	20	12	60.00%	36.05%	80.88%	0	0.00%	0	0.00%	8	40.00%	0.6000
C	20	19	95.00%	75.13%	99.87%	0	0.00%	0	0.00%	1	5.00%	0.9500

Between Appraiser Agreement:	# Inspected	# Matched	Percent	95% LC	95% UC
	20	10	50.00%	27.20%	72.80%

All Appraisers vs Standard Agreement:	# Inspected	# Matched	Percent	95% LC	95% UC	Cohen's Kappa
	20	10	50.00%	27.20%	72.80%	0.8000

Notes for use of the Attribute Gage R&R (MSA) Template:

1. Attribute Gage R&R is also known as Attribute Agreement Analysis.

2. Recommend for study: 3 Appraisers, 2 Repeats, Minimum of 10 Good Parts and 10 Bad Parts. The data should be balanced with each appraiser evaluating the same number of parts and the same number of repeats.

3. Specify the Good Part or Unit as "G" or other appropriate text ("P", "Y", etc.). Specify the Bad Part or Unit as "NG" or other appropriate text ("F", "N", etc.). Be careful to avoid typing or spelling errors when entering the results. A space accidentally inserted after a character will be treated as a different value leading to incorrect results.

Process Sigma Calculator – Discrete Data Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Process Sigma Discrete**.

Process Sigma Calculator - Discrete Data		
Number of Units Processed	N	1000
Total Number of Defects	D	10
Number of Defect Opportunities per Unit	O	1
Defects per million opportunities	dpmo	10000.0
Defects as percentage		1.00%
Process Sigma Level	Sigma	3.83

Notes for use of the Process Sigma Calculator for Discrete Data:

1. Total number of defects should include defects made and later fixed.
2. Sigma level incorporates 1.5 sigma shift.
3. Sample size should be large enough to observe 5 defects. P is estimate of proportion for outcome of interest. Use P = 0.5 if unknown.

Process Sigma Calculator – Continuous Data Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Process Sigma Continuous**.

Process Sigma Calculator - Continuous Data

Enter Mean:	X-bar	0
Enter Standard Deviation:	S	1
Enter USL:		3
Enter LSL:		-3
	Expected ppm > USL	1350.0
	Expected % > USL	0.13%
	Expected ppm < LSL	1350.0
	Expected % < LSL	0.13%
	Yield %	99.73%
	Sigma Level	4.28

Notes for use of the Process Sigma Calculator for Continuous Data:

1. This calculator assumes that the Mean and Standard Deviation are computed from data that is normally distributed.

2. Sigma Level incorporates a 1.5 sigma shift.

Process Capability Indices Calculator – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Capability Indices**.

Calculate Process Capability Indices: Cp, Cpk; Pp, Ppk		
Enter Mean:	X-Bar	0
Enter Standard Deviation:	S	1
Enter USL:		3
Enter LSL:		-3
	Cp, Pp	1.00
	Cpk, Ppk	1.00
	Cpu, Ppu	1.00
	Cpl, Ppl	1.00

Notes for use of the Process Capability Indices Calculator:

1. This calculator assumes that the Mean and Standard Deviation are computed from data that is normally distributed.

2. Reports Cp, Cpk if entered S is Within or Short Term (using a control chart).

3. Reports Pp, Ppk if entered S is Overall or Long Term.

Process Capability & Confidence Intervals Calculator – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **Capability Indices & CI**.

Calculate Confidence Interval for Sigma, Cp, Cpk; Pp, Ppk			
Enter Mean:		X-Bar	0
Enter Standard Deviation:		S	1
Enter Size of sample:		n	30
Confidence level (enter as percent):		100*(1-α)%	95.00%
Enter USL:			3
Enter LSL:			-3
Lower Limit Sigma	0.79641	Cpu, Ppu	1.00
Upper Limit Sigma	1.34432	Cpl, Ppl	1.00
Cp, Pp	1.00	Cpk, Ppk	1.00
Lower Limit Cp, Pp	0.74	Lower Limit Cpk, Ppk	0.72
Upper Limit Cp, Pp	1.26	Upper Limit Cpk, Ppk	1.28

Notes for use of the Process Capability Indices Calculator:

1. This calculator assumes that the Mean and Standard Deviation are computed from data that is normally distributed.

2. Reports Cp, Cpk if entered S is Within or Short Term (using a control chart).

3. Reports Pp, Ppk if entered S is Overall or Long Term.

Standard Deviation Confidence Interval Calculator – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **CI Sigma**.

Calculate Confidence Interval for Sigma

Enter Standard Deviation:	S	1
Enter Size of Sample:	n	30
Confidence level (enter as a percent):	100*(1-α)%	95.00%
	Lower Limit Sigma	0.796406988
	Upper Limit Sigma	1.344316063

One Proportion Confidence Interval Calculator – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **1 Proportion CI**.

Confidence Interval for One Proportion

Number of elements in category of interest:	X	10
Size of Sample:	n	100
Confidence level(enter as a percent):	100*(1-α)%	95.00%
	p = X/n	0.1
	Lower Limit (exact)	0.049004674
	Upper Limit (exact)	0.176222801
	Lower Limit (normal)	0.041201116
	Upper Limit (normal)	0.158798884

Two Proportions Test Calculator – Example

Open the file **Template & Calculator Examples.xls**. Click on the worksheet named **2 Proportions Test**.

Hypothesis Test for the Equality of Two Proportions

Number of elements in sample #1 in category of interest:	x1	70
Size of Sample #1:	n1	100
Number of elements in sample #2 in category of interest:	x2	80
Size of Sample #2:	n2	100
	p1 = x1/n1	0.7
	p2 = x2/n2	0.8
	Zo Statistic	1.633
	P-Value (2-tail)	0.102

Part C – Descriptive/Summary Statistics

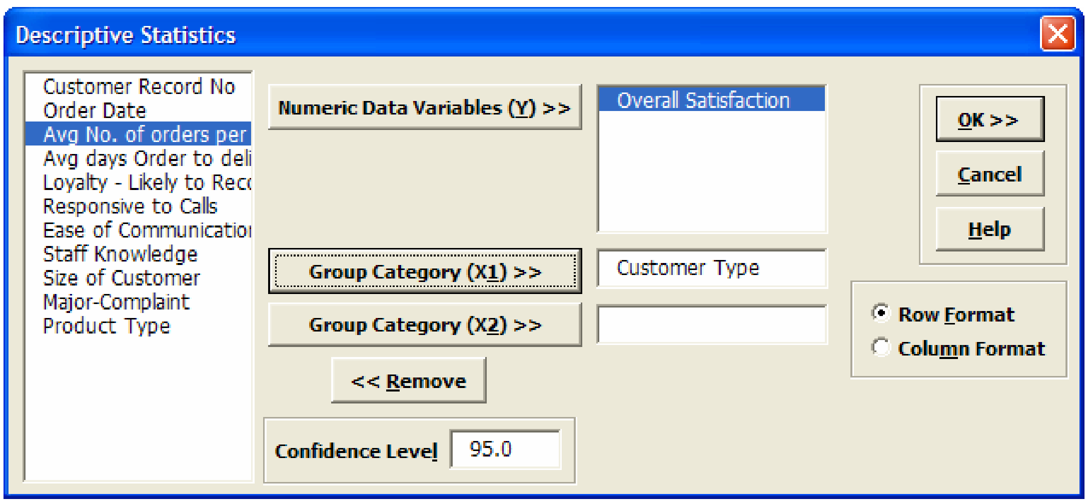
Descriptive Statistics

1. Open **Customer Data.xls.** Click Sheet 1 Tab.

2. Click SigmaXL > Statistical Tools > Descriptive Statistics

3. Check "Use Entire Data Table", click Next

4. Select Overall Satisfaction, click Numeric Data Variables (Y) >>. Select Customer Type, click Group Category (X1) >> as shown:



5. Click OK

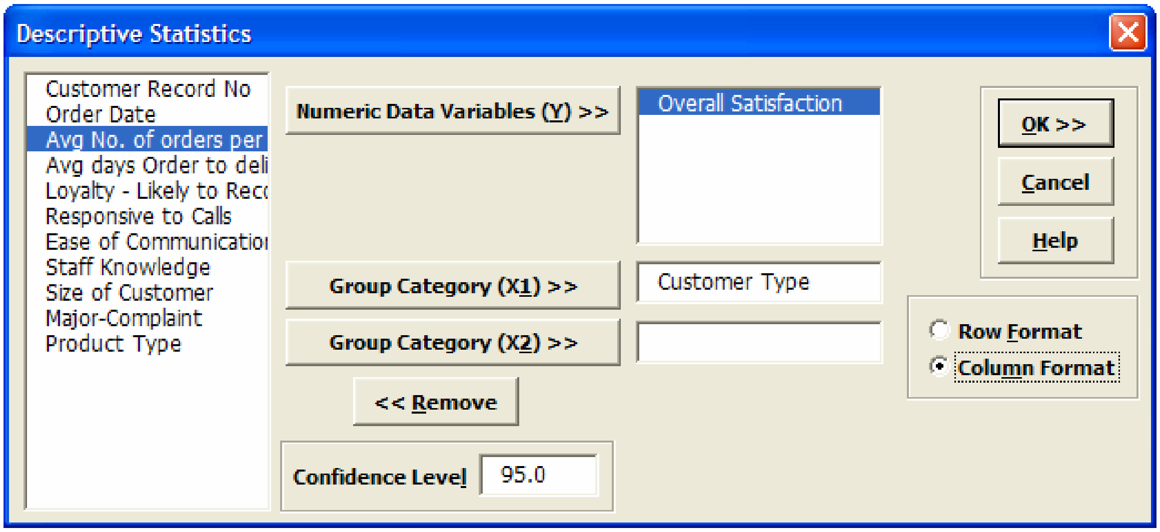
6. Descriptive Statistics are given for Customer Satisfaction broken out by Customer Type:

Overall Satisfaction by Customer Type			
	Customer Type = 1	Customer Type = 2	Customer Type = 3
Count	31	42	27
Mean	3.3935	4.2052	3.6411
Stdev	0.824680	0.621200	0.670478
Range	3.0800	2.5600	2.7400
Minimum	1.7200	2.4200	2.1900
25th Percentile (Q1)	2.8100	3.8275	3.2400
50th Percentile (Median)	3.5600	4.3400	3.5100
75th Percentile (Q3)	4.0200	4.7250	4.1700
Maximum	4.8000	4.9800	4.9300
95.0% CI Mean	3.091054 to 3.696043	4.011659 to 4.398818	3.375879 to 3.906344
95.0% CI Sigma	0.659012 to 1.102328	0.511126 to 0.792132	0.528013 to 0.918845
Anderson-Darling Normality Test	A-Squared = 0.312776; P-Value = 0.5306	A-Squared = 0.826259; P-Value = 0.0302	A-Squared = 0.389291; P-Value = 0.3600

Which Customer Type has the highest satisfaction score? Clearly Type 2. However we have to be careful concluding that there is a significant difference in satisfaction solely by looking at the Means. In the Analyze Phase we will run tests of hypothesis to validate that Type 2 Customers are, in fact, significantly more satisfied.

Tip: Click on Column B, click Window > Split, Window > Freeze Panes. This freezes Column A and allows you to scroll across the Descriptive Statistics for each level of the Group Category. This is particularly beneficial when there are a large number of columns.

7. Click "Recall SigmaXL Dialog" menu or press **F3** to recall last dialog. Change the format selected to Column Format as shown:



8. Click OK. Descriptive Statistics are given for Customer Satisfaction broken out by Customer Type in Column Format:

Overall Satisfaction by Customer Type	Count	Mean	Stdev	Range	Minimum	25th Percentile (Q1)	50th Percentile (Median)	75th Percentile (Q3)	Maximum	95.0% CI Mean	95.0% CI Sigma
Customer Type = 1	31	3.3935	0.824680	3.0800	1.7200	2.8100	3.5600	4.0200	4.8000	3.091054 to 3.696043	0.659012 to 1.102328
Customer Type = 2	42	4.2052	0.621200	2.5600	2.4200	3.8275	4.3400	4.7250	4.9800	4.011659 to 4.398818	0.511126 to 0.792132
Customer Type = 3	27	3.6411	0.670478	2.7400	2.1900	3.2400	3.5100	4.1700	4.9300	3.375879 to 3.906344	0.528013 to 0.918845

Tip: This column format is useful to create subsequent graphs on the summary statistics.

Part D – Histograms

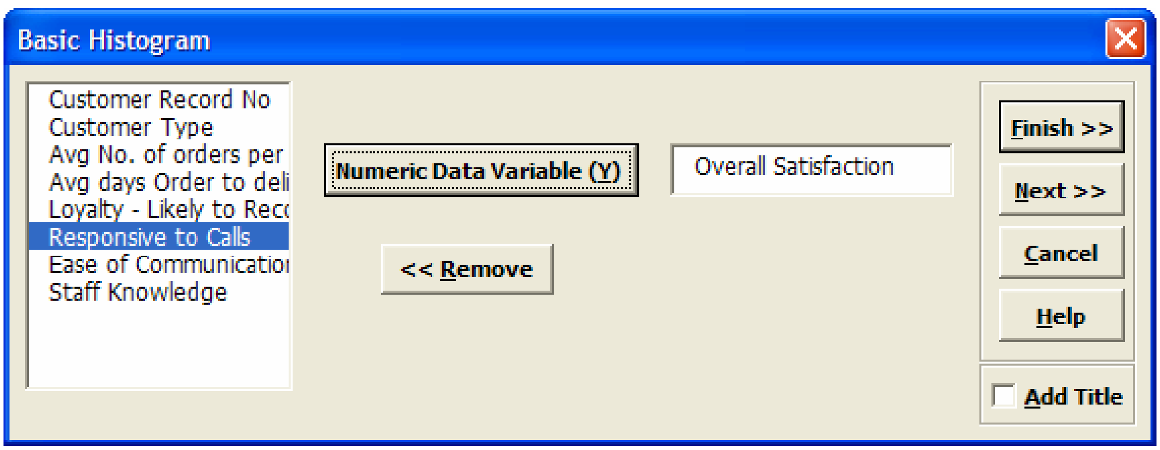
Single (Basic) Histogram

1. Click Sheet 1 Tab of **Customer Data.xls** (or press **F4** to activate last worksheet).

2. Click SigmaXL > Graphical Tools > Basic Histogram

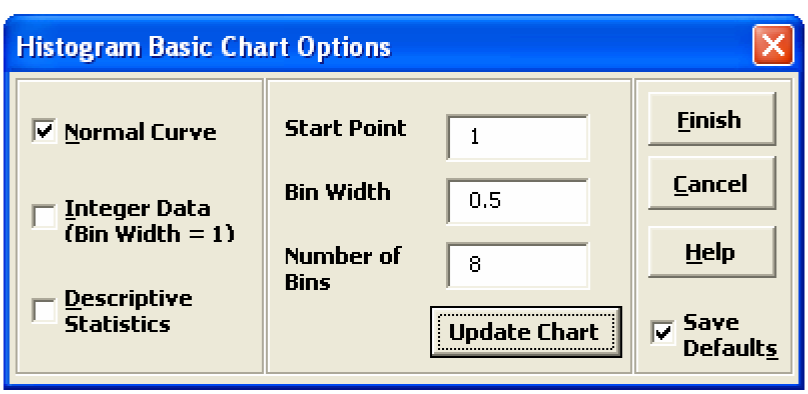
3. Ensure that entire data table is selected. If not, check “Use Entire Data Table”. Click Next.

4. Select Overall Satisfaction, click Numeric Data Variable (Y) >> as shown:

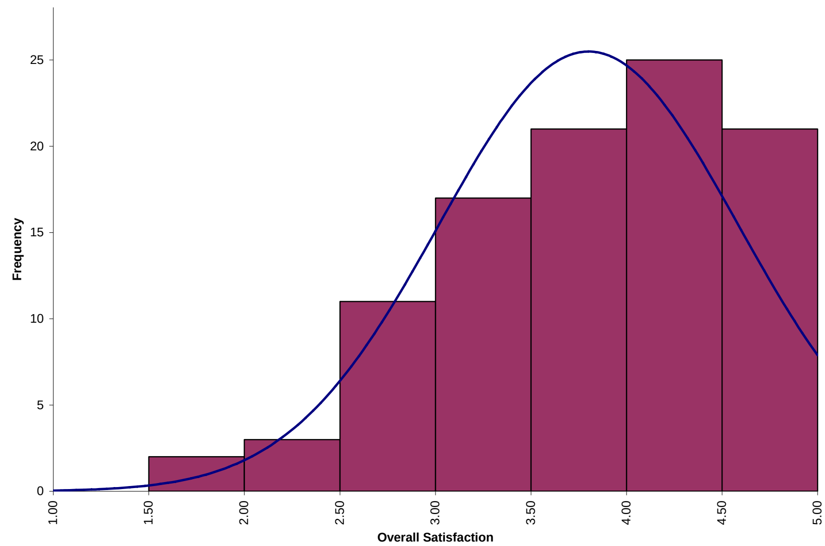


5. Click Next.

6. Check Normal Curve. Set Start Point = 1. Change the Bin Width to 0.5, and the number of bins to 8. Click Update Chart to view the histogram. (If the survey satisfaction data was pure integer format we would have checked the Integer Data option).



7. Click Finish. A histogram of Overall Customer Satisfaction is produced.



8. Note that bin one is 1 to < 1.5, bin 2 is 1.5 to < 2, etc.

   Tip: Any graph produced by SigmaXL can be copied/pasted into Word. It can also be enlarged by clicking on the graph and dragging the corner. The number of decimal places displayed can be modified by clicking on the axis label and selecting the Number tab to adjust. The text label alignment can also be modified by selecting the Alignment tab.

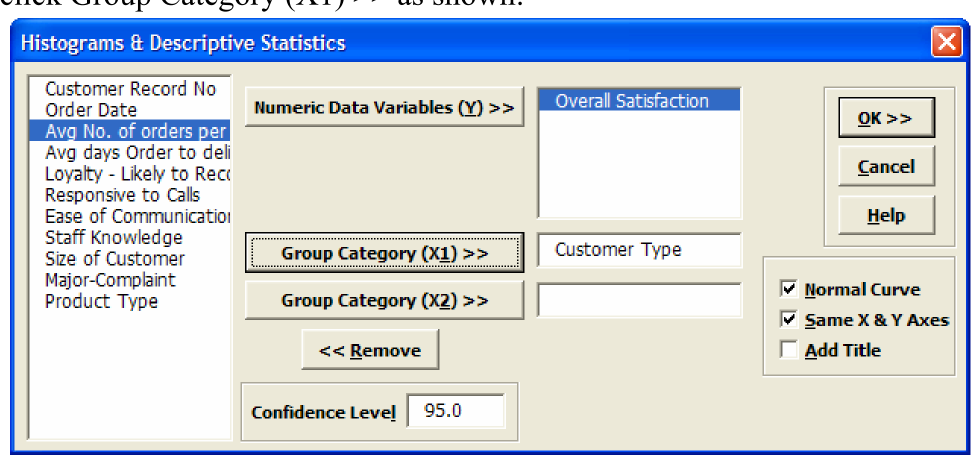
Multiple Histograms

1. Click Sheet 1 Tab of **Customer Data.xls** (or press **F4** to activate last worksheet).

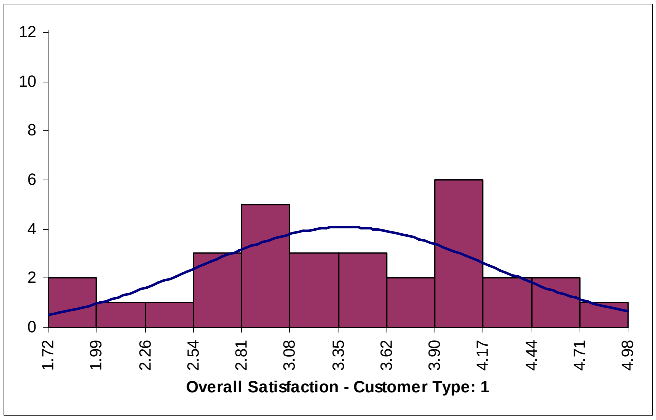
2. Click SigmaXL > Graphical Tools > Histograms & Descriptive Statistics.

3. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

4. Select Overall Satisfaction, click Numeric Data Variables (Y) >>, select Customer Type, click Group Category (X1) >> as shown:



5. Click OK. Multiple Histograms and Descriptive Statistics of Customer Satisfaction By Customer Type are produced:



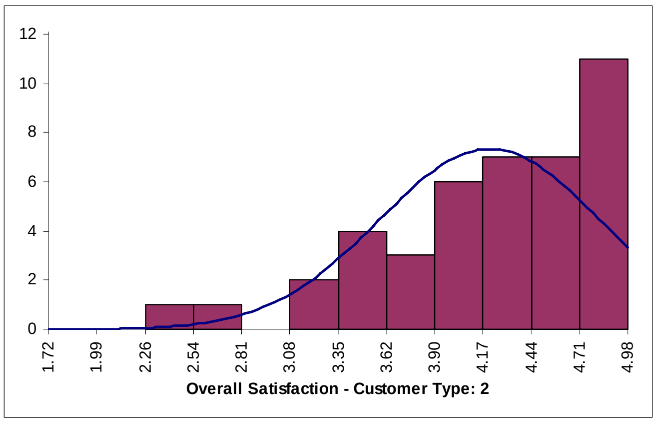
Overall Satisfaction - Customer Type: 1

Count = 31
Mean = 3.3935
Stdev = 0.824680
Range = 3.1

Minimum = 1.7200
25th Percentile (Q1) = 2.8100
50th Percentile (Median) = 3.5600
75th Percentile (Q3) = 4.0200
Maximum = 4.8

95% CI Mean = 3.09 to 3.7
95% CI Sigma = 0.659012 to 1.102328

Anderson-Darling Normality Test:
A-Squared = 0.312776; P-value = 0.5306



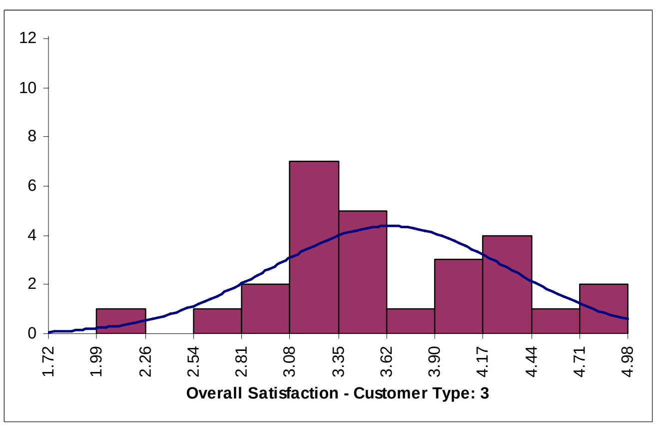
Overall Satisfaction - Customer Type: 2

Count = 42
Mean = 4.2052
Stdev = 0.621200
Range = 2.6

Minimum = 2.4200
25th Percentile (Q1) = 3.8275
50th Percentile (Median) = 4.3400
75th Percentile (Q3) = 4.7250
Maximum = 4.98

95% CI Mean = 4.01 to 4.4
95% CI Sigma = 0.511126 to 0.792132

Anderson-Darling Normality Test:
A-Squared = 0.826259; P-value = 0.0302



Overall Satisfaction - Customer Type: 3

Count = 27
Mean = 3.6411
Stdev = 0.670478
Range = 2.7

Minimum = 2.1900
25th Percentile (Q1) = 3.2400
50th Percentile (Median) = 3.5100
75th Percentile (Q3) = 4.1700
Maximum = 4.93

95% CI Mean = 3.38 to 3.9
95% CI Sigma = 0.528013 to 0.918845

Anderson-Darling Normality Test:
A-Squared = 0.389291; P-value = 0.3600

Clearly Customer Type 2 shows a higher level of overall satisfaction, with the data skewed left. Note that Customer Type 1 and 3 have data that is normally distributed, but this is not desirable when the response is a satisfaction score!

6. Note that bin one is 1.72 to < 1.99, bin 2 is 1.99 to < 2.26, etc. The number of decimals displayed can be changed by double-clicking on the X axis, click Number tab, and adjust decimal places.

Part E – Boxplots

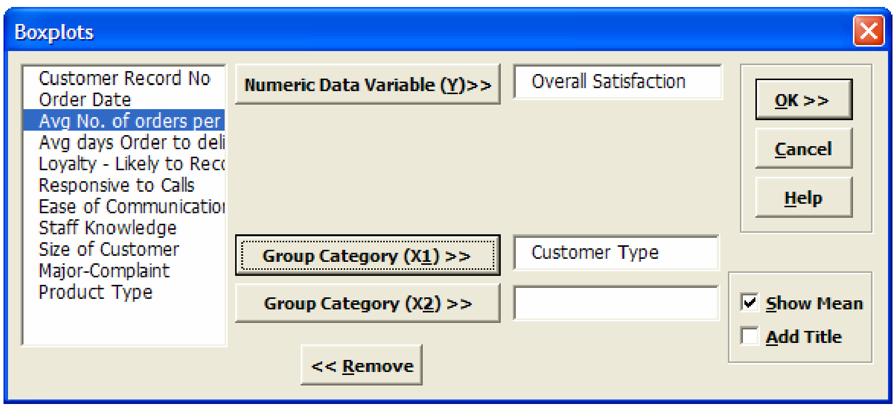
Boxplots

1. Click Sheet 1 Tab of **Customer Data.xls** (or press **F4** to activate last worksheet).

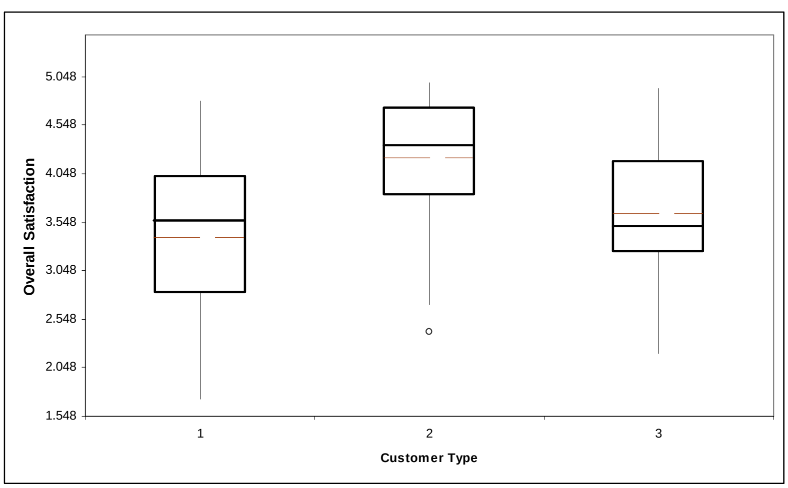
2. Click SigmaXL > Graphical Tools > Boxplots

3. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

4. Select Overall Satisfaction, click Numeric Data Variable (Y) >>, select Customer Type, click Group Category (X1) >>, check Show Mean:



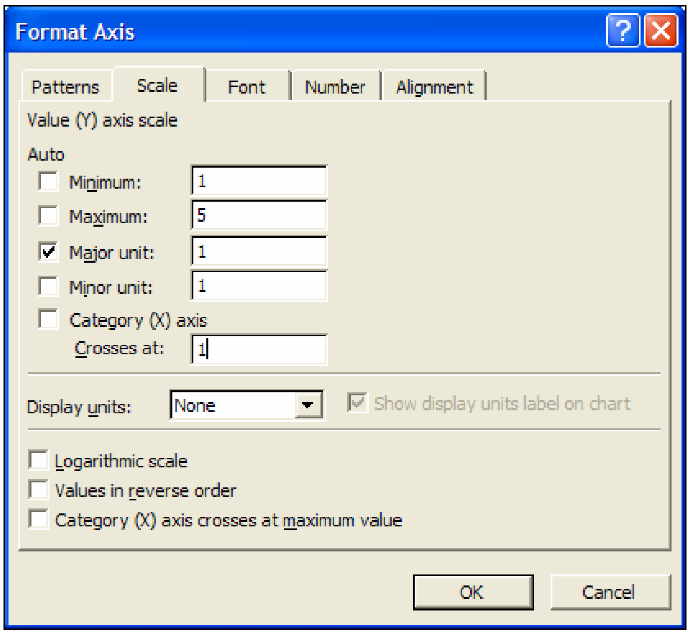
5. Click OK. A boxplot of Customer Satisfaction By Customer Type is produced:



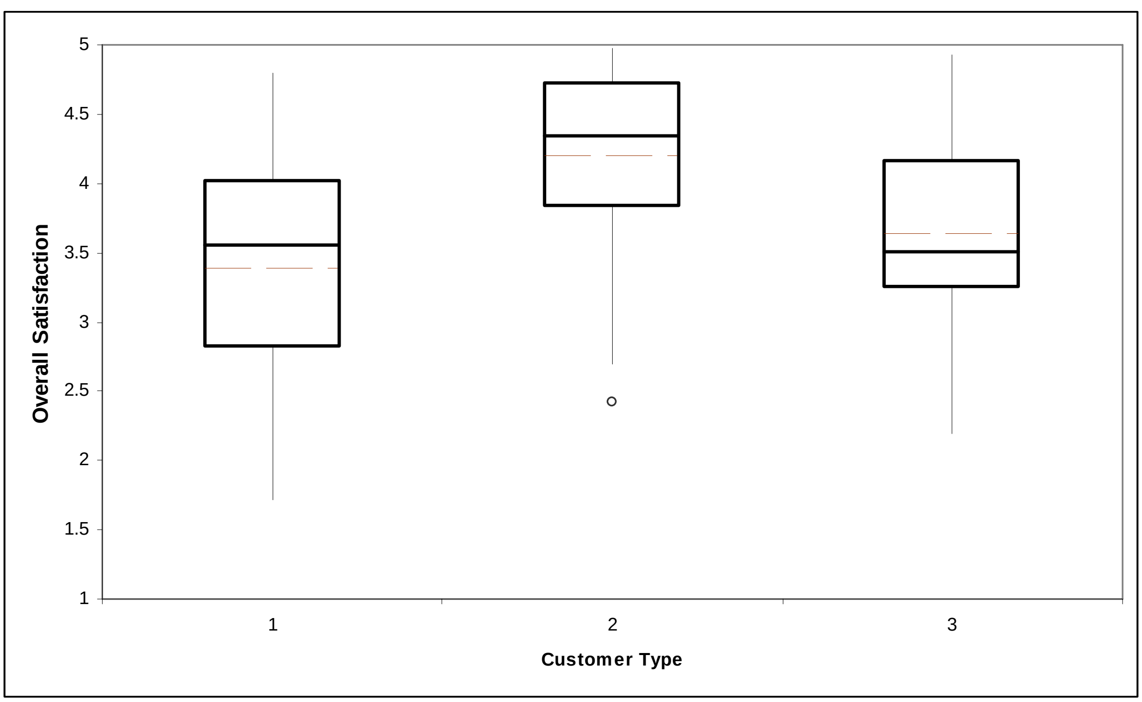
6. The solid center line is the median. The dashed red line shows the sample mean. The top of the box is the 75th percentile (Q3). The bottom of the box is the 25th percentile (Q1). The height of the box is called the Inter-Quartile Range (IQR) and is a robust measure of spread

or sample variability. The data point highlighted for Customer Type 2 is a potential outlier. Note that extreme outliers are highlighted with a solid dot.

7. Now we will modify the Y axis scale, showing 1 as minimum and 5 as maximum (given that the response data comes from a survey with 1-5 scale). To do this double click on the Y axis, select Scale, modify the minimum value and maximum value. Change category (X) axis crosses at: to 1 as shown:

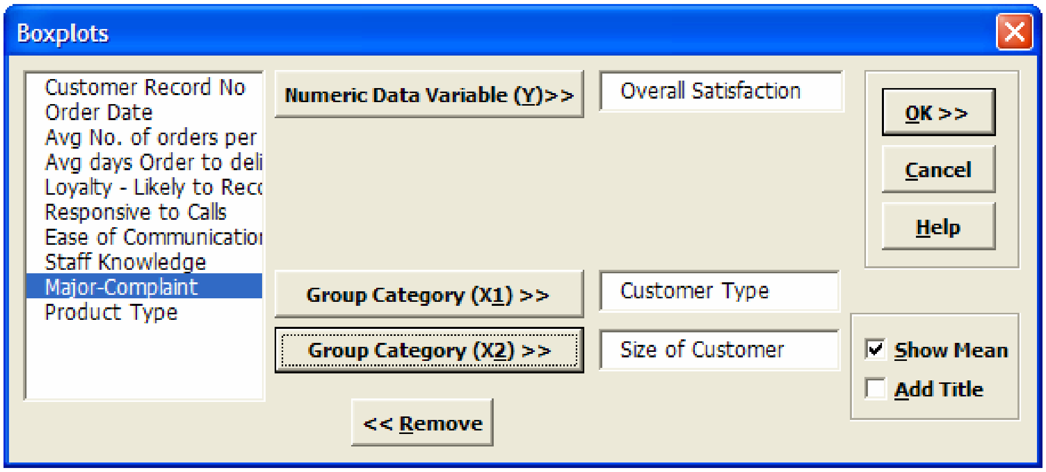


8. Click OK. The Boxplot axis is modified as shown below:

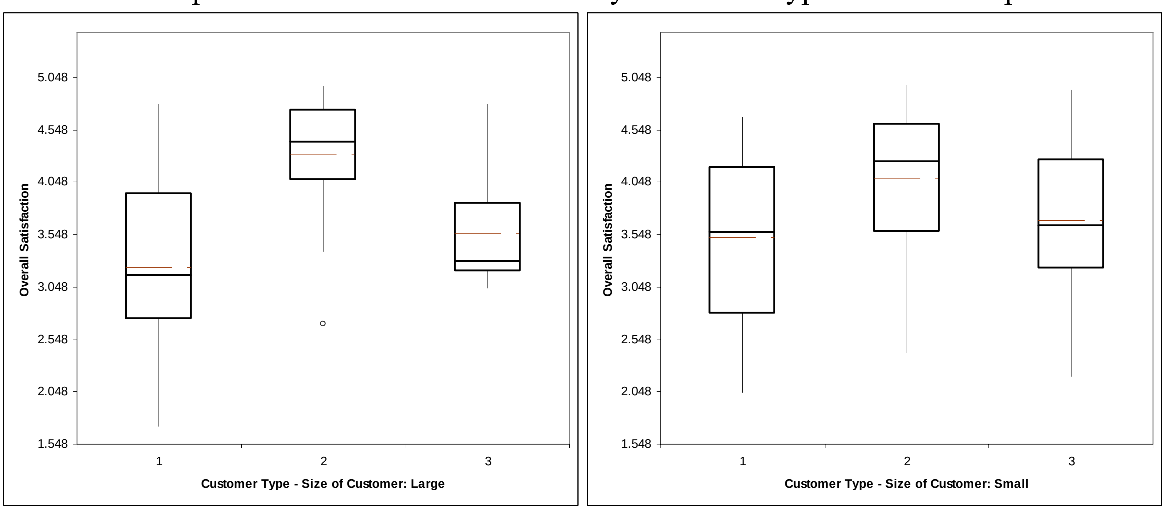


9. Click "Recall SigmaXL Dialog" menu or press **F3** to recall last dialog.

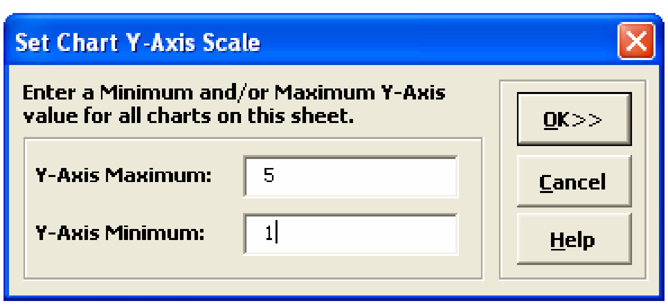
10. Select Overall Satisfaction as the Numeric Data Variable (Y) ; select Customer Type as Group Category (X1) and Size of Customer as Group Category (X2); check Show Mean:



11. Click OK. Boxplots of Customer Satisfaction By Customer Type and Size are produced:



12. In order to adjust the Y-axis scale for both charts click SigmaXL Chart Tools > Set Chart Y-Axis Max/Min.

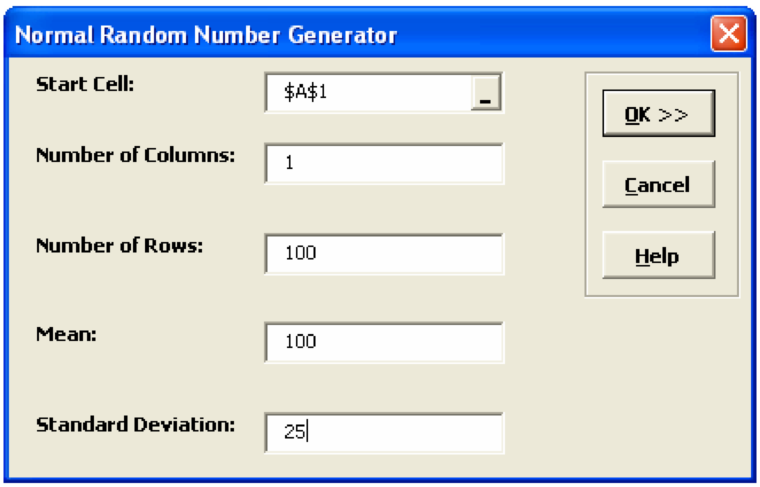


13. Click OK. The Y-axis scale maximum and minimum are now modified for both charts.

Part F – Normal Probability Plots

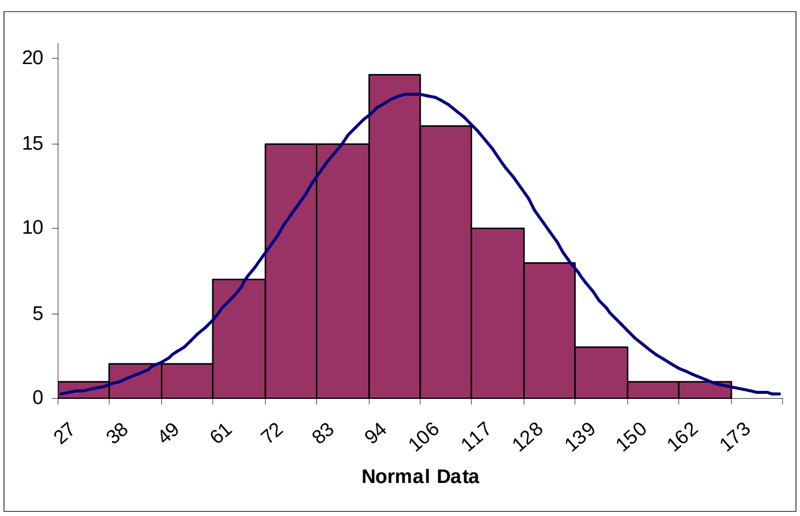
Normal Probability Plots

1. Create 100 random normal values as follows: Click SigmaXL > Data Manipulation > Normal Random Data. Specify 1 column, 100 rows, mean of 100 and standard deviation of 25 as shown below:



2. Click OK. Change Column heading to "Normal Data"

3. Create a Histogram & Descriptive Statistics for this data. Your data will be slightly different due to the random number generation:



Normal Data

Count = 100
Mean = 98.796
Stdev = 24.990
Range = 134.7

Minimum = 26.938
25th Percentile (Q1) = 78.947
50th Percentile (Median) = 97.125
75th Percentile (Q3) = 114.74
Maximum = 161.63

95% CI Mean = 93.84 to 103.8
95% CI Sigma = 21.94 to 29.03

Anderson-Darling Normality Test:
A-Squared = 0.24378; P-value = 0.7587

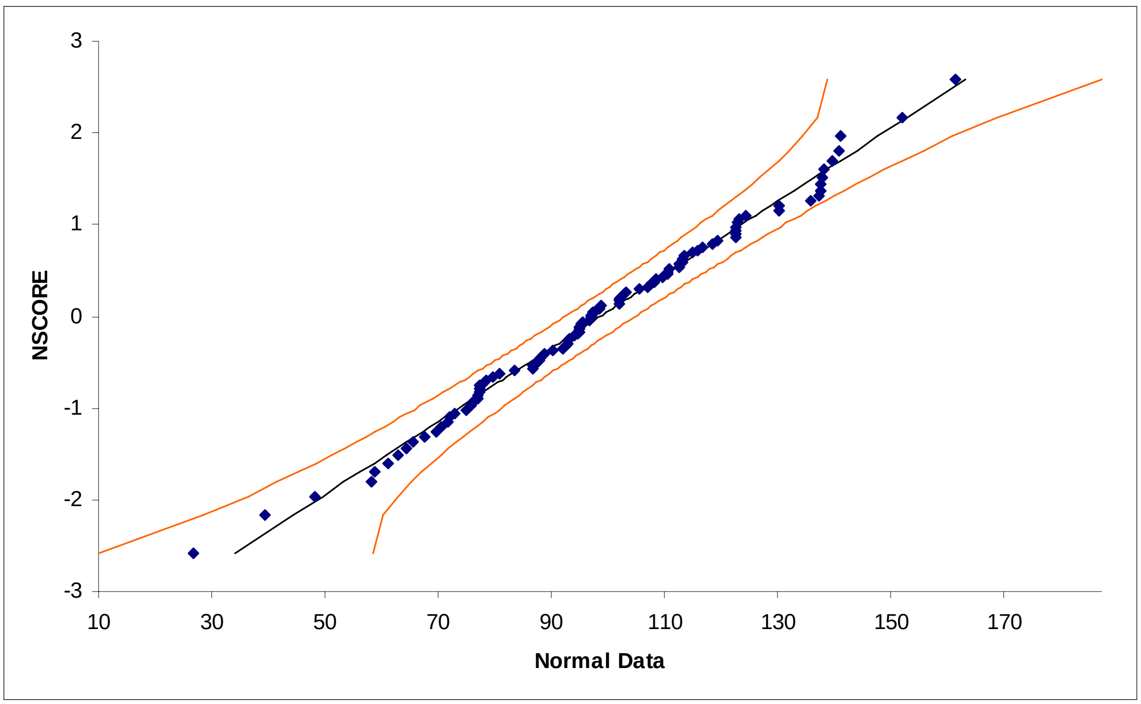
If the p-value of the Anderson-Darling Normality test is greater than or equal to .05, the data is considered to be normal (interpretation of p-values will be discussed further in Analyze).

4. Create a normal probability plot of this data: Click Normal Random Data (1) Sheet, Click SigmaXL > Graphical Tools > Normal Probability Plots.

5. Ensure that Normal Data column is selected, click Next.

6. Select Normal Data as Numeric Data Variable (Y). Check Add Titles. Enter “Example Normal Prob Plot”.

7. Click OK. Normal Probability Plot of simulated random data is produced:



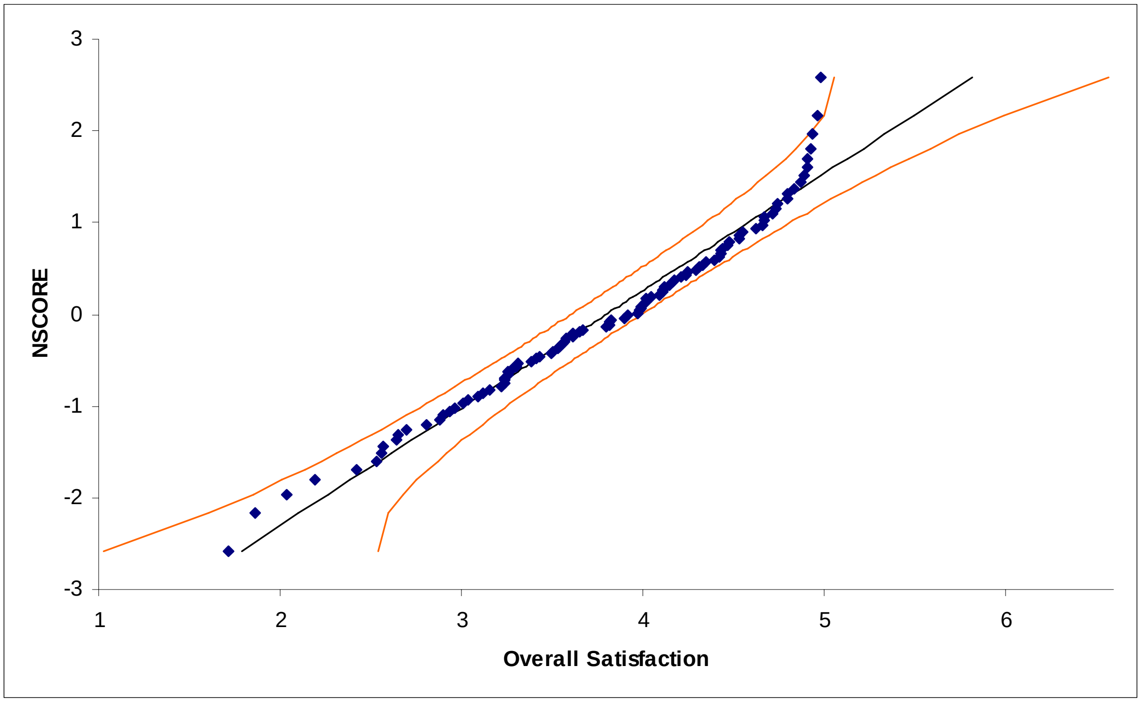
The data points follow the straight line fairly well, indicating that the data is normally distributed. Note that the data will not likely fall in a perfectly straight line. The eminent statistician George Box uses a “Fat Pencil” test where the data, if covered by a fat pencil, can be considered normal! We can also see that the data is normal since the points fall within the normal probability plot 95% confidence intervals (confidence intervals will be discussed further in Analyze).

8. Click Sheet 1 Tab of **Customer Data.xls**

9. Click SigmaXL > Graphical Tools > Normal Probability Plots

10. Ensure that entire data table is selected. If not, check “Use Entire Data Table”. Click Next.

11. Select Overall Satisfaction as Numeric Data Variable (Y). Click OK. Normal Probability Plot of Customer Satisfaction data is produced:

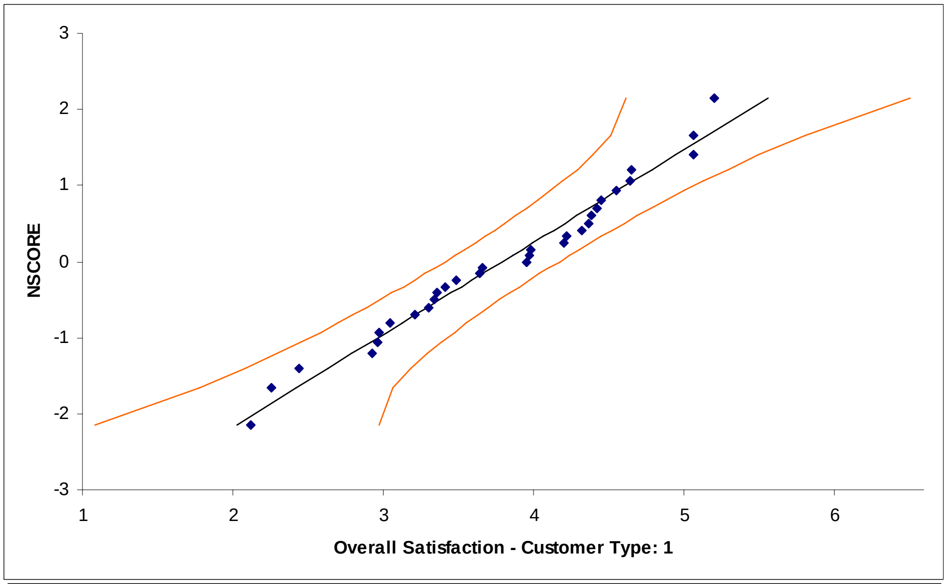


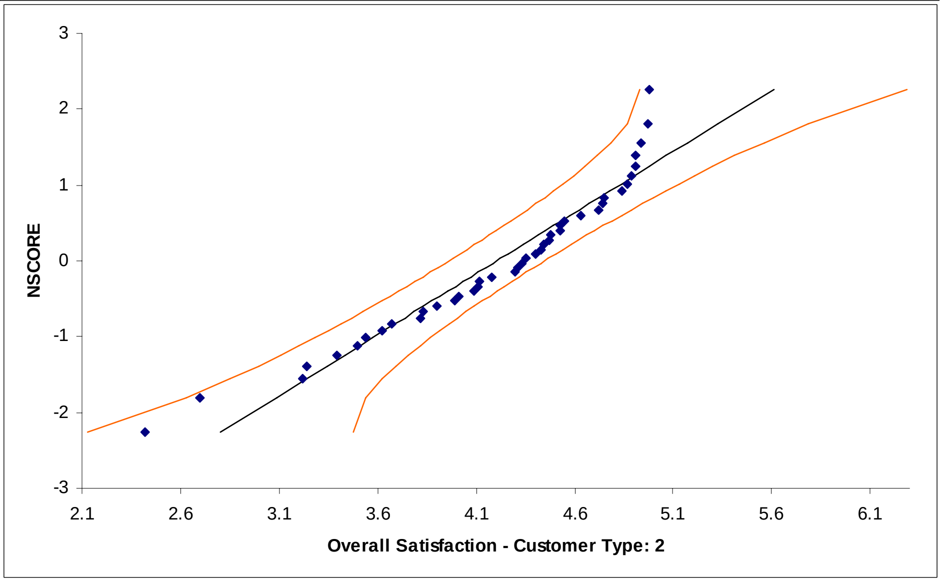
Is this data normally distributed? See earlier histogram and descriptive statistics of Customer Satisfaction data.

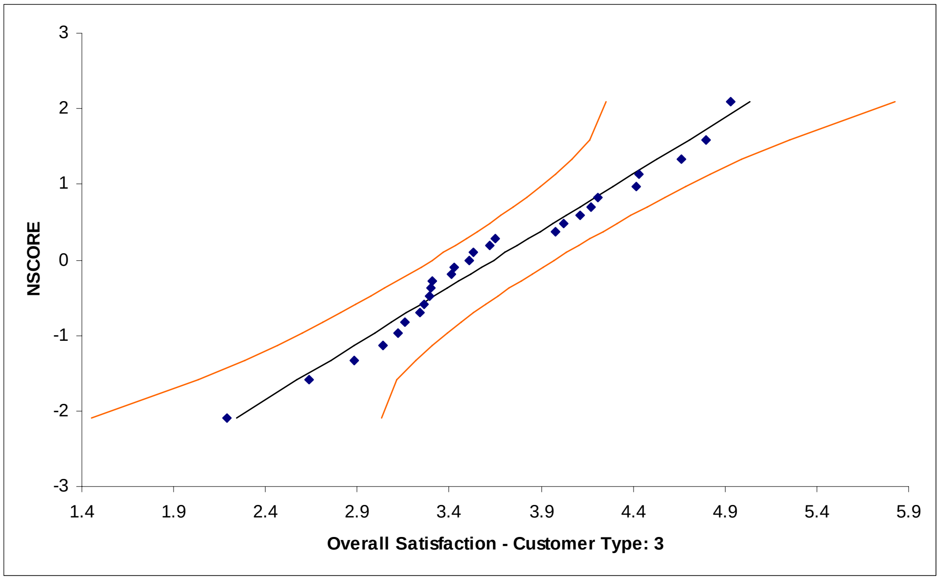
12. Now we would like to stratify the customer satisfaction score by customer type and look at the normal probability plots.

13. Click Sheet 1 of **Customer Data.xls**. Click SigmaXL > Graphical Tools > Normal Probability Plots. Ensure that Entire Table is selected, click Next. (Alternatively press **F3** or click Recall SigmaXL Dialog to recall last dialog).

14. Select Overall Satisfaction as Data Variable (Y), Customer Type as Group Category (X). Click OK. Normal Probability Plots of Overall Satisfaction by Customer Type are produced:


NSCORE
3
2
1
0
-1
-2
-3
1
2
3
4
5
6
Overall Satisfaction - Customer Type: 1


NSCORE
3
2
1
0
-1
-2
-3
2.1
2.6
3.1
3.6
4.1
4.6
5.1
5.6
6.1
Overall Satisfaction - Customer Type: 2


NSCORE
3
2
1
0
-1
-2
-3
1.4
1.9
2.4
2.9
3.4
3.9
4.4
4.9
5.4
5.9
Overall Satisfaction - Customer Type: 3

Reviewing these normal probability plots, along with the previously created histograms and descriptive statistics, we see that the satisfaction data for customer type 2 is not normal, and skewed left, which is desirable for satisfaction data! Note that although the customer type 2 data falls within the 95% confidence intervals, the Anderson Darling test from descriptive statistics shows $p < .05$ indicating non-normal data. Smaller sample sizes tend to result in wider confidence intervals, but we still see that the curvature for customer type 2 is quite strong.

Tip: Use the Normal Probability Plot (NPP) to distinguish reasons for non-normality. If the data fails the Anderson Darling (AD) test (with $p < 0.05$) and forms a curve on the NPP, it is inherently non-normal or skewed. Calculations such as Sigma Level, Pp, Cp, Ppk, Cpk assume normality and will therefore be affected. Consider transforming the data using LN(Y) or SQRT(Y) or using the Box-Cox Transformation tool (SigmaXL > Data Manipulation > Box-Cox Transformation) to make the data normal. Of course, whatever transformation you apply to your data, you must also apply to your specification limits.

If the data fails the AD normality test, but the bulk of the data forms a straight line and there are some outliers, the outliers are driving the non-normality. Do not attempt to transform this data! Determine the root cause for the outliers and take corrective action on those root causes.

Part G – Run Charts

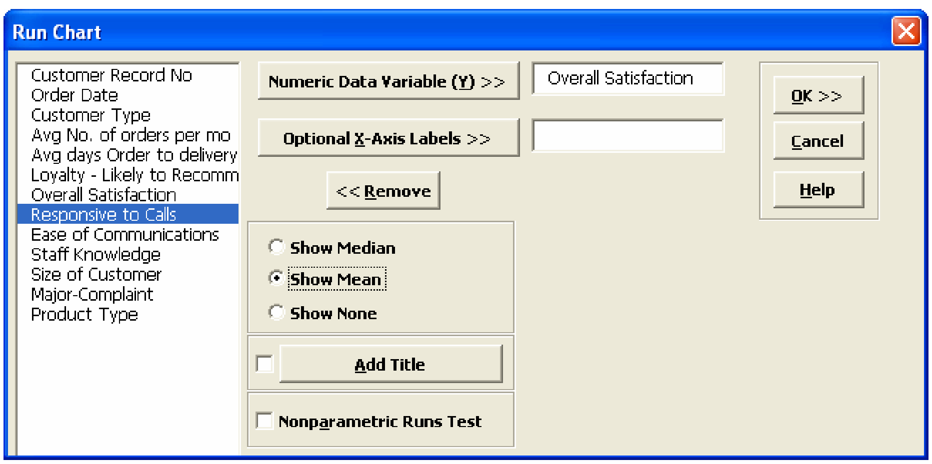
Run charts, also known as trend charts and time series plots, add the dimension of time to the graphical tools. They allow us to see trends and outliers in the data. Run Charts are a precursor to control charts, which add calculated control limits. Note that Run Charts should be used only on unsorted data, in its original chronological sequence.

Run Charts

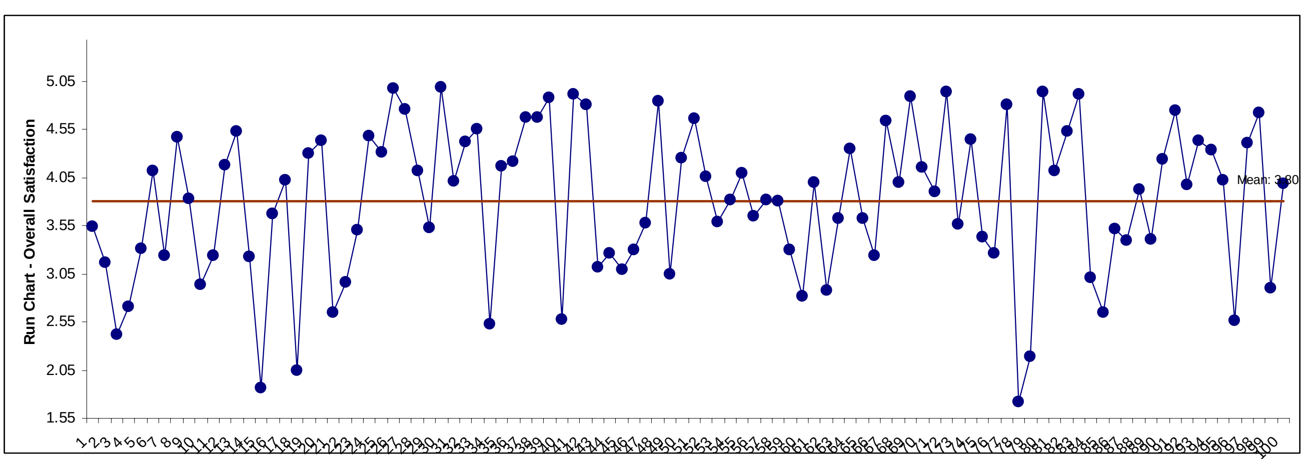
1. Click Sheet 1 Tab of **Customer Data.xls** (or press **F4** to activate last worksheet). Click SigmaXL > Graphical Tools > Run Chart.

2. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

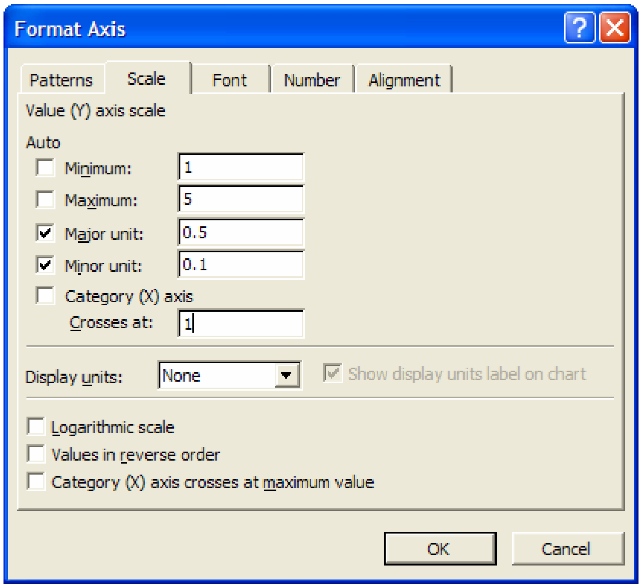
3. Select Overall Satisfaction, click Numeric Data Variable (Y) >>. Select "Show Mean". Uncheck Nonparametric Runs Test (this will be discussed later in Part M of Analyze Phase).



4. Click OK. A Run Chart of Overall Satisfaction with Mean center line is produced.

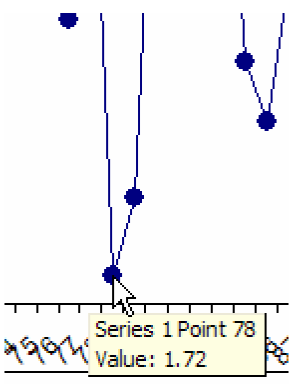


5. Double click on the Y axis to activate the Format Axis dialog. Select the Scale tab, change Minimum to 1, Maximum to 5., Category X Axis Crosses at 1:

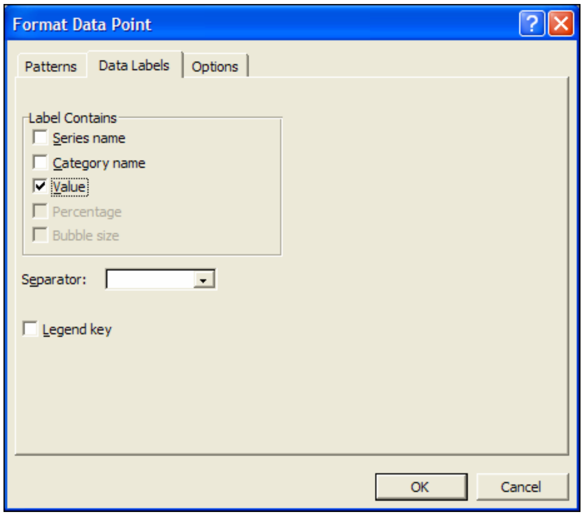


6. Click OK.

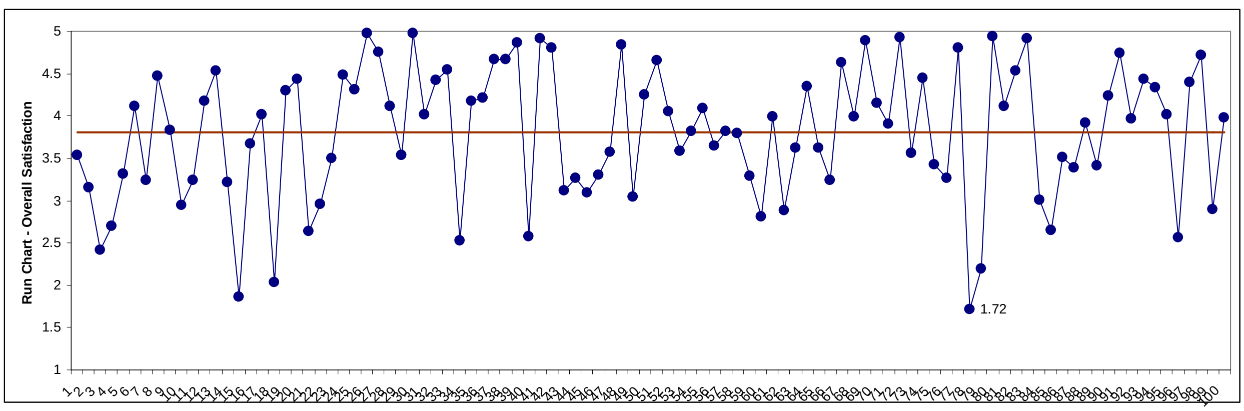
7. Are there any obvious trends? Some possible cycling, but nothing clearly stands out. It may be interesting to look more closely at a specific data point. Any data point value can be identified by simply moving the cursor over it:



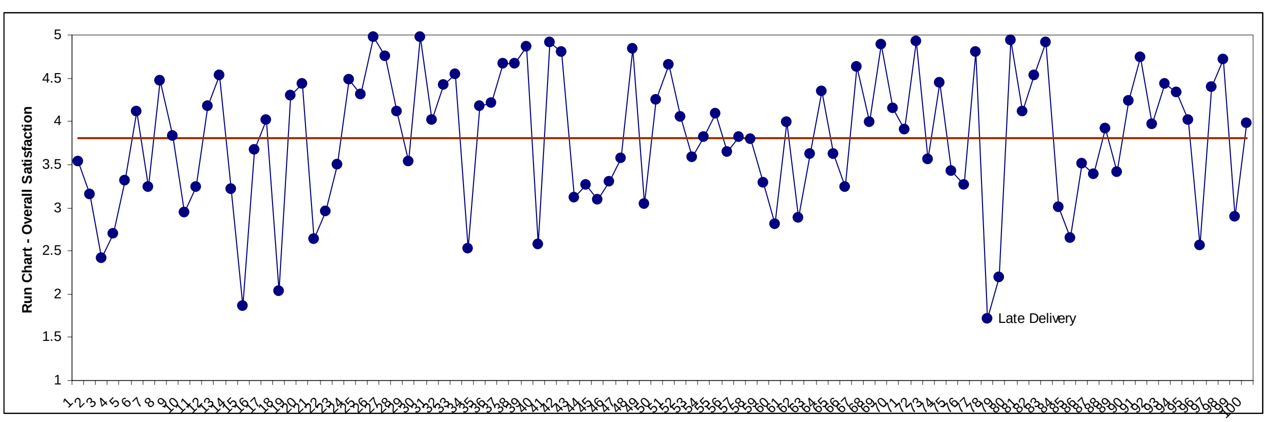
8. A label can be added to a data point by two single-clicks (not a double-click) on the data point, followed by a right mouse click, and select Format Data Point. Select Data Labels tab, check value.



9. Click OK. Resulting Run Chart with label attached to data point:



10. This label can be changed to a text comment. Single-click three times on the label and type in a comment as shown:



Part H – Process Capability

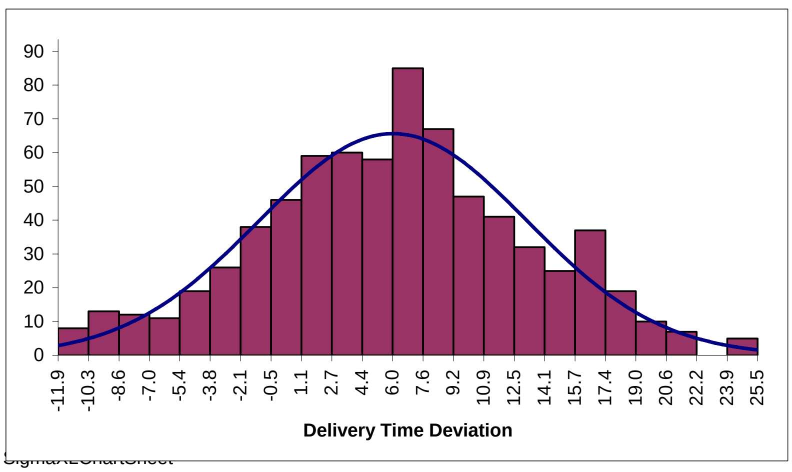
Process Capability

1. Open the file **Delivery Times.xls**. This contains continuous data of hotel breakfast delivery times. Deviation Time is the deviation around targeted delivery time in minutes. The Critical Customer Requirements (CCR's) are as follows: USL = 10 minutes late, LSL = -10 minutes (early).

2. Let's begin with a view of the data using Histograms and Descriptive Statistics. Click SigmaXL > Graphical Tools > Histograms & Descriptive Statistics.

3. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

4. Select Delivery Time Deviation as the Numeric Data Variable (Y). Click OK.



Delivery Time Deviation

Count = 725
Mean = 6.0036
Stdev = 7.1616
Range = 37.3

Minimum = -11.900
25th Percentile (Q1) = 1.2991
50th Percentile (Median) = 6.2998
75th Percentile (Q3) = 10.666
Maximum = 25.4493

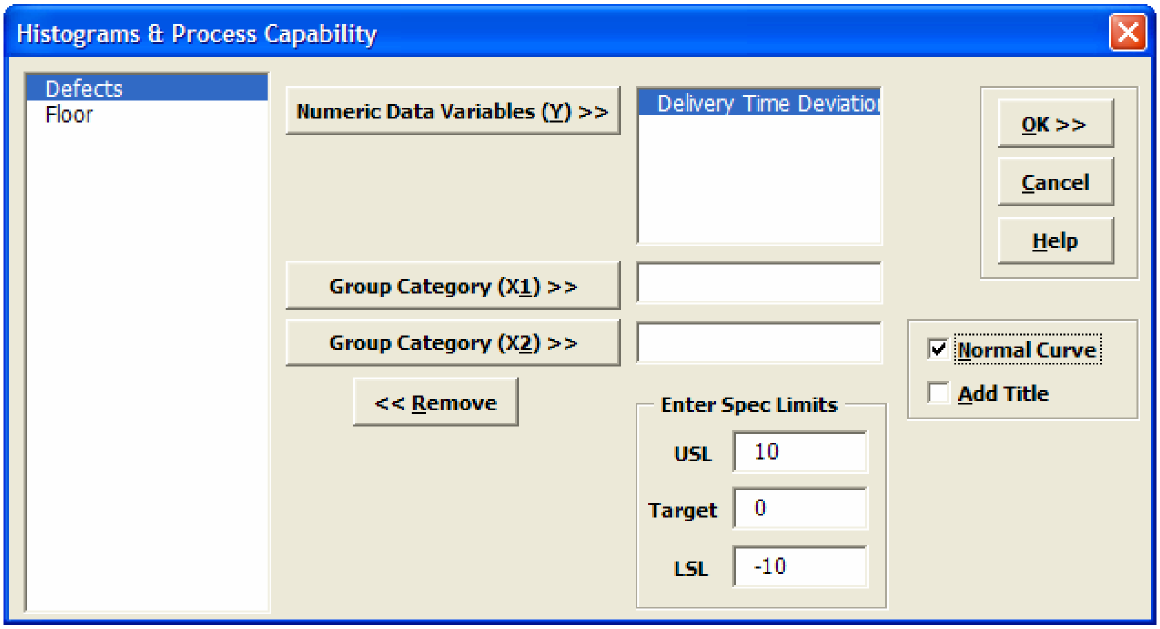
95% CI Mean = 5.48 to 6.5
95% CI Sigma = 6.810972 to 7.550533

Anderson-Darling Normality Test:
A-Squared = 0.708616; P-value = 0.0641

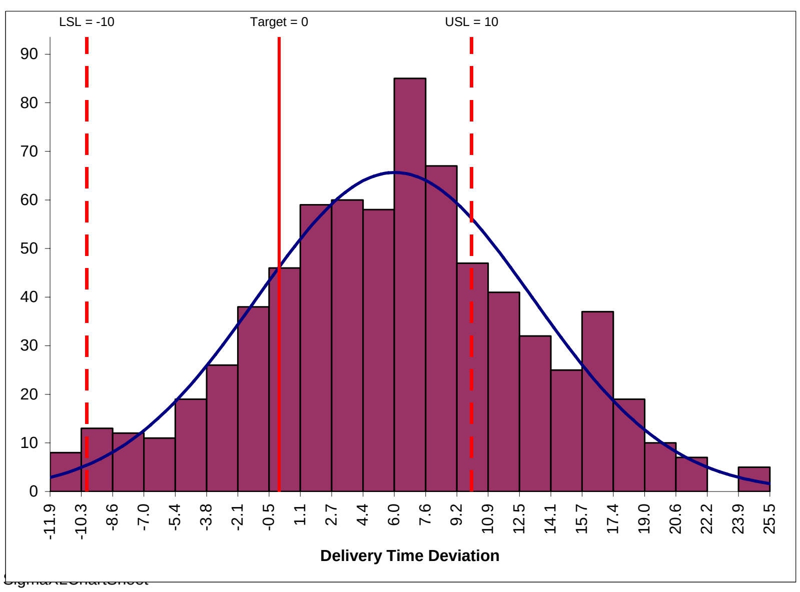
Note that the data has an average of 6, so on average the breakfast delivery is 6 minutes late. Also note the wide variation in delivery times (Stdev = 7.2 minutes). With the AD p-value > .05, this data can be assumed to have a normal distribution.

5. Click Sheet 1 Tab. Click SigmaXL > Graphical Tools > Histograms & Process Capability.

6. Select Delivery Time Deviation as the Numeric Data Variable (Y). Enter USL = 10, Target = 0, LSL = -10, check Normal Curve as shown below:



7. Click OK. Resulting Histogram & Process Capability report is shown below:



Delivery Time Deviation

Count = 725.00
Mean = 6.00
Stdev (Overall) = 7.16
USL = 10.00
Target = 0.00
LSL = -10.00

Capability Indices using Overall Standard Deviation
Pp = 0.47
Ppu = 0.19
Ppl = 0.74
Ppk = 0.19
Cpm = 0.36

Expected Overall Performance
ppm > USL = 288409.3
ppm < LSL = 12720.5
ppm Total = 301129.8
% > USL = 28.84%
% < LSL = 1.27%
% Total = 30.11%

Actual (Empirical) Performance
% > USL = 26.90%
% < LSL = 1.38%
% Total = 28.28%

With the Process Performance indices Pp and Ppk < 1, this process is clearly in need of improvement. Note that the difference between Pp and Ppk is due to the off-center process mean. (Cp and Cpk indices are optionally provided when creating Control Charts – these will be demonstrated later in the Control Phase).

Process Capability for Non-Normal Data (Box-Cox Transformation)

An important assumption for Process Capability analysis is that the data be normally distributed. The Box-Cox Transformation tool is used to convert non-normal data to normal by applying a power transformation. Box-Cox Power Transformation applies automatic power transformations to data, Y^lambda, where lambda varies from -5 to +5. You may select rounded or optimal lambda for storage of the transformed data. Rounded is typically preferred since it will result in a more "intuitive" transformation such as Ln(Y) (lambda=0) or SQRT(Y) (lambda=0.5).

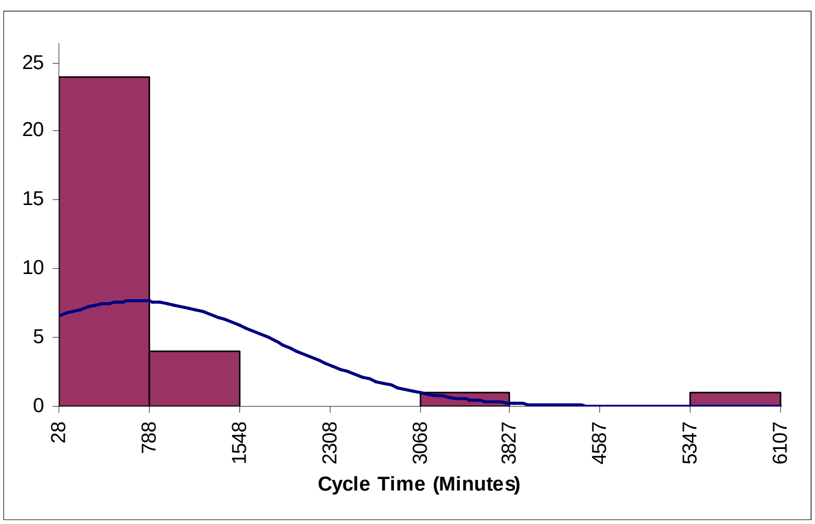
The Anderson-Darling normality test is applied to the transformed data so that you can immediately see whether or not the final transformation results in normal data. Box-Cox is particularly effective for skewed data but will not work on bimodal data, nor should it be used on data where the "non-normality" is due to outliers.

1. Open the file **Non-Normal Cycle Time.xls**. This contains continuous data of process cycle times. The Critical Customer Requirement is: USL = 1000 minutes.

2. Let's begin with a view of the data using Histograms and Descriptive Statistics. Click SigmaXL > Graphical Tools > Histograms & Descriptive Statistics.

3. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

4. Select Cycle Time (Minutes) as the Numeric Data Variable (Y). Click OK.



Cycle Time (Minutes)

Count = 30
Mean = 687.40
Stdev = 1186.9
Range = 6073.0

Minimum = 28
25th Percentile (Q1) = 175.25
50th Percentile (Median) = 361.50
75th Percentile (Q3) = 578.50
Maximum = 6101

95% CI Mean = 244.21 to 1130.6
95% CI Sigma = 945.2441 to 1595.549

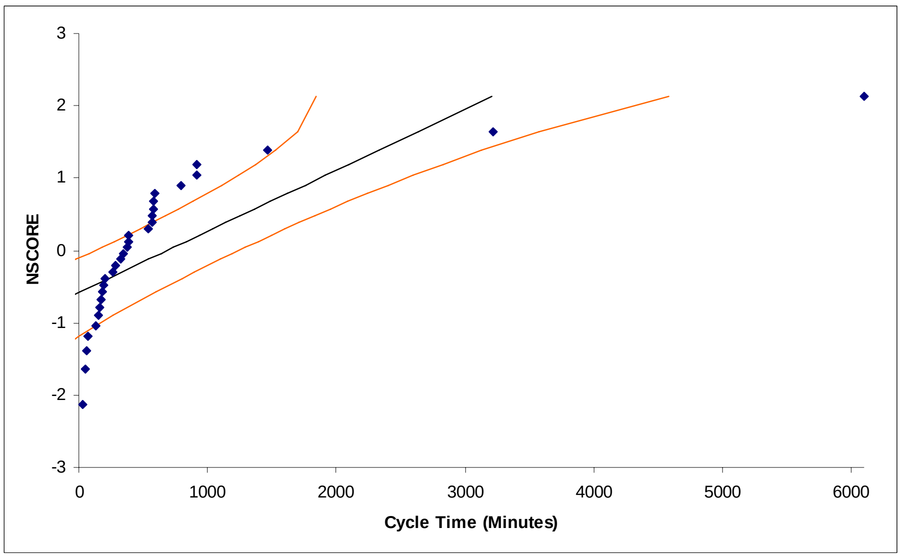
Anderson-Darling Normality Test:
A-Squared = 5.286481; P-value = 0.0000

Clearly this is a process in need of improvement. To start, we would like to get a baseline process capability. The problem with simply repeating the above Capability analysis is that the results will be incorrect due to the non-normality in the data. The Histogram and AD p-value < .05 clearly show that this data is not normal.

5. We will confirm the non-normality by using a Normal Probability Plot. Click Sheet 1 Tab (or **F4**). Click SigmaXL > Graphical Tools > Normal Probability Plots.

6. Ensure that the entire data table is selected. If not, check "Use Entire Data Table". Click Next.

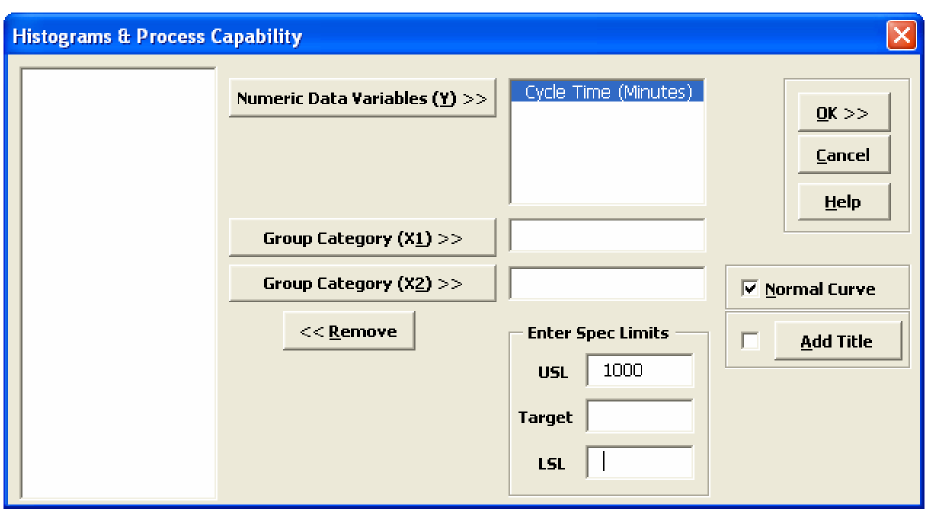
7. Select Cycle Time (Minutes) as the Numeric Data Variable (Y). Click OK. A Normal Probability Plot of Cycle Time data is produced:



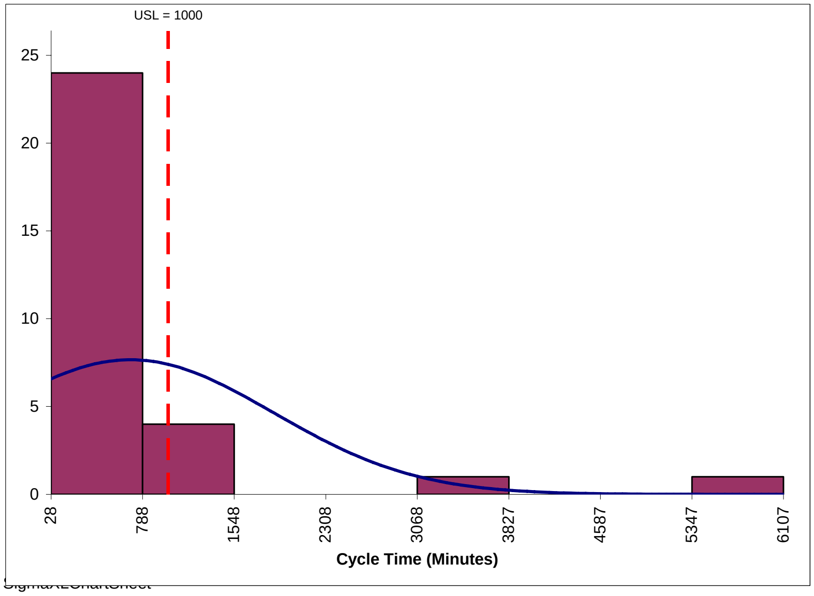
8. The curvature in this normal probability plot confirms that this data is not normal. (Note that the X axis scale minimum was manually set to 0).

9. For now, let us ignore the non-normality issue and proceed with the Process Capability study. Click Sheet 1 Tab. Click SigmaXL > Graphical Tools > Histograms & Process Capability.

10. Select Cycle Time (Minutes) as the Numeric Data Variable (Y). Enter USL = 1000, Delete previous Target and LSL settings.



11. Click OK. The resulting Process Capability Report is shown below:



Cycle Time (Minutes)

Count = 30.00
Mean = 687.40
Stdev (Overall) = 1186.89
USL = 1000.00
Target =
LSL =

Capability Indices using Overall Standard Deviation
Pp =
Ppu = 0.09
Ppl =
Ppk = 0.09
Cpm =

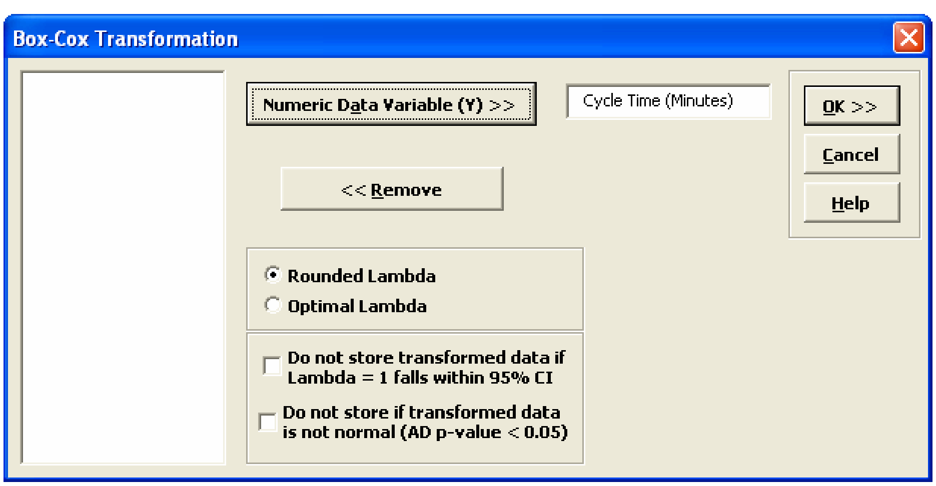
Expected Overall Performance
ppm > USL = 396129.5
ppm < LSL =
ppm Total = 396129.5
% > USL = 39.61%
% < LSL =
% Total = 39.61%

Actual (Empirical) Performance
% > USL = 10.00%
% < LSL =
% Total = 10.00%

Notice the discrepancy between the Expected Overall (Theoretical) Performance and Actual (Empirical) Performance. This is largely due to the non-normality in the data; the expected performance assumes that the data is normal. Since this assumption is not true, why not just use the empirical performance and disregard the theoretical? This would not work here because the sample size, n = 30 is too small to estimate performance using pass/fail (discrete) criteria.

12. We will now attempt to transform the data using the Box-Cox Power Transformation tool. Click Sheet 1 Tab (or **F4**). Click SigmaXL > Data Manipulation > Box-Cox Transformation. Ensure that the entire data table is selected. If not, check "Use Entire Data Table". Click Next.

13. Select Cycle Time (Minutes) as the Numeric Data Variable (Y).



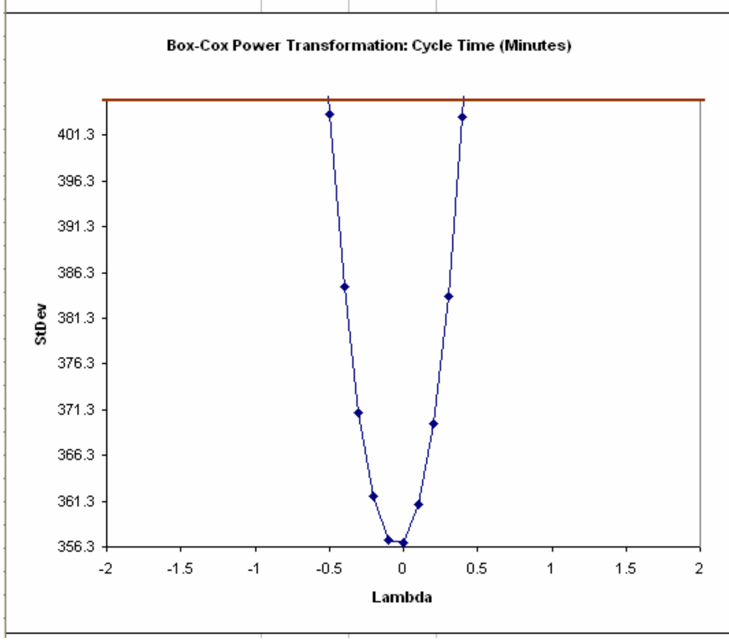
Tip: The selected variable must contain all positive values. If this is not the case, add a shift factor to all of the data equal to: -(minimum value) + 1. Keep in mind that further analysis will require compensation for this shift factor.

Tip: Note that while this tool is often successful to transform the data to normality, there may not be a suitable transformation to make the data normal. The output report indicates the Anderson-Darling p-value for the transformed data. You may wish to check “Do not store if transformed data is not normal”. Another option is “Do not store transformed data if Lambda = 1 falls within 95%CI”. This latter option prevents you from using transformations that do not result in a statistically significant improvement towards normality.

14. Click OK. The resulting report is shown:

Box-Cox Power Transformation: Cycle Time (Minutes)

Optimal Lambda	-0.04
Final Lambda	0
UC Lambda (95%)	0.407756
LC Lamda (95%)	-0.506879
Anderson Darling Normality Test for Transformed Data:	
A-Squared	0.326821
AD P-value	0.5063

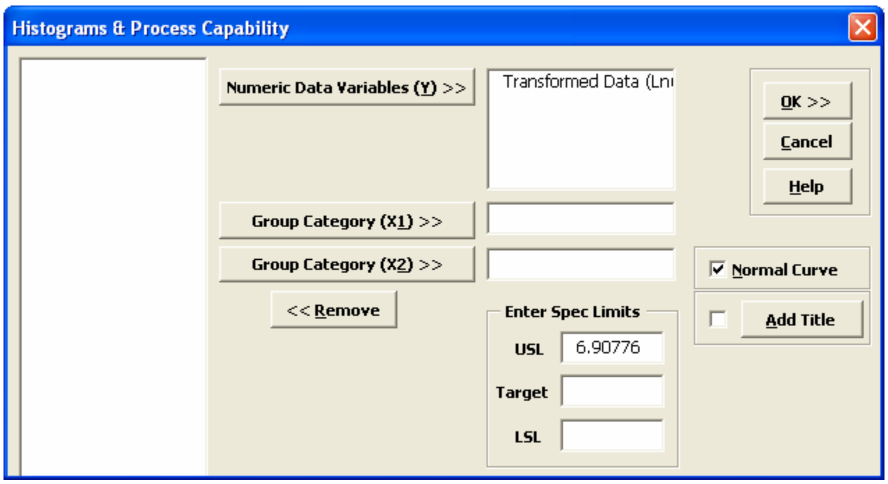


Cycle Time (Minutes)	Transformed Data (Ln(Y))
3216	8.07589363
261	5.564520407
392	5.97126184
63	4.143134726
28	3.33220451
6101	8.716207971
151	5.017279837
46	3.828641396
1465	7.289610521
383	5.948034989
287	5.659482216
322	5.774551546
538	6.28785856
574	6.352629396
586	6.37331979
920	6.82437367
178	5.18178355
129	4.859812404
187	5.231108617
71	4.262679877
342	5.834810737
167	5.117993812
794	6.677083461
205	5.323009979
576	6.356107661
575	6.354370041
381	5.942799375
576	6.356107661
918	6.822197391
190	5.247024072

15. The fact that Lambda=1 falls outside of the 95% confidence interval tells us that the transformation is statistically significant. The Anderson-Darling p-value of 0.5063 indicates that we cannot reject the null hypothesis that the transformed data is normal, so the Ln transformation has successfully converted the data to normality.

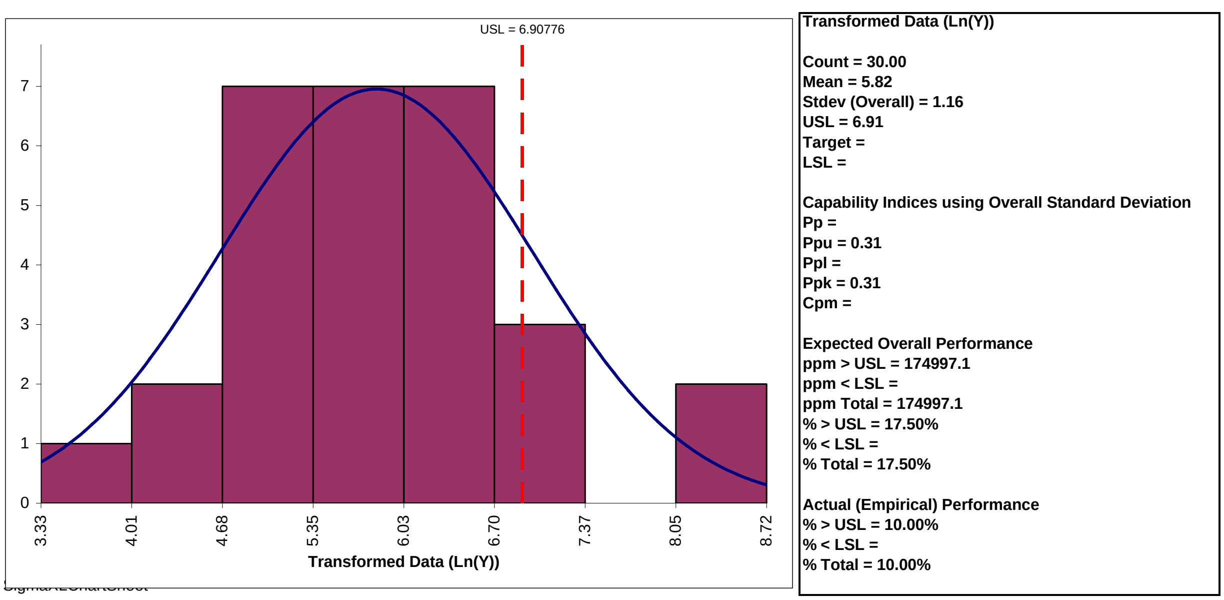
16. Before we run the Process Capability report on the transformed data, we need to calculate the transformed specification limit. In this case the final lambda was rounded from -.04 to 0, which denotes a natural log transformation. So the proper entry for our specification limit will be Ln(1000) = 6.90776. This can be calculated in an Excel cell using the formula "=LN(1000)".

17. Select cells G1:G31. Click SigmaXL > Graphical Tools > Histograms & Process Capability. Select Transformed Data (Ln(Y)) as the Numeric Data Variable (Y). Enter USL = 6.90776.



Tip: If the Final Lambda is negative, be sure to reference the original USL as transformed LSL, and original LSL as transformed USL.

18. Click OK. The resulting Process Capability report is shown:



19. Note that the Expected Overall Performance is closer to the Actual (Empirical) Performance. We can now use the 17.5% defective rate as our baseline level.

20. Entering the transformed Mean, Standard Deviation, and Specification Limits into the Sigma Level Calculator (SigmaXL > Templates and Calculators > Process Sigma – Continuous), gives us a Sigma Level of 2.43.

Process Sigma Calculator - Continuous Data

Enter Mean:	X-bar	5.8242
Enter Standard Deviation:	S	1.1594
Enter USL:		6.9078
Enter LSL:		
	Expected ppm > USL	174991.7
	Expected % > USL	17.50%
	Expected ppm < LSL	
	Expected % < LSL	
	Yield %	82.50%
	Sigma Level	2.43

SigmaXL: Analyze Phase Tools

Part A – Stratification with Pareto

SigmaXL's Pareto tool allows you to create Basic (Single) or Advanced (Multiple) Pareto Charts. Advanced Pareto charts are particularly useful in the Analyze Phase because of the ease with which you can slice and dice (or stratify) your data. Of course, Pareto charts are not limited to the Analyze Phase – they can also be used to aid project selection and to prioritize in the Measure Phase.

Consider the following guidelines to help ensure that your Pareto analysis is successful:

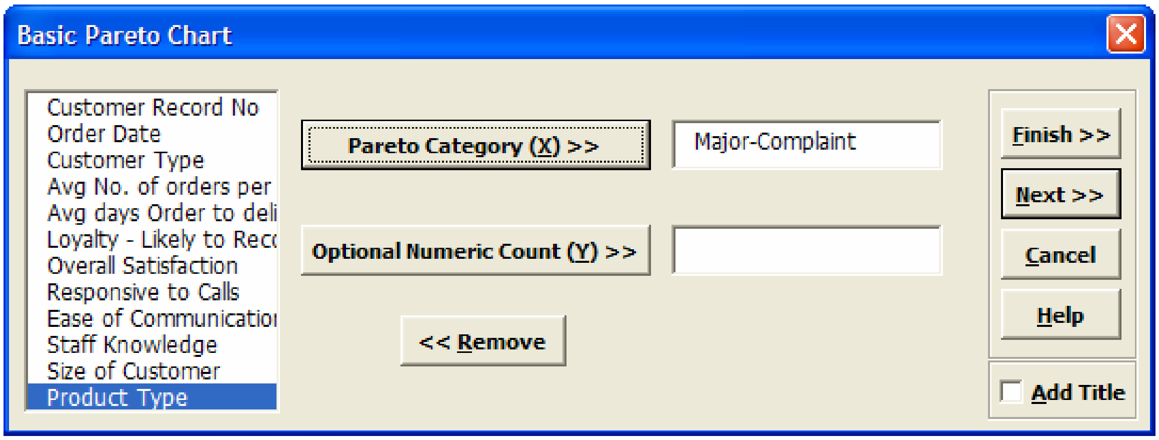
- Your Pareto analysis will only be as good as the quality of the data collected. Ensure that you have the right data and that the data is correct. Use other graphs such as run charts to apply a sanity check to your data.
- Check process stability using appropriate control charts. If the process is not in control, your prioritization of defects and root causes could be invalid.
- Avoid collecting data over too short a time period. Your data may not be representative of the process as a whole.
- Conversely, data gathered over too long a time period may include process changes that could lead to incorrect conclusions. SigmaXL provides a date subsetting feature that allows you to easily explore different time periods.
- If your initial Pareto analysis does not yield useful results, explore other categories that may be important. SigmaXL's Advanced Charts makes it easy for you to 'slice and dice' your data with different X categories.
- Consider Pareto charting measures such as cost and severity, in addition to defect counts. SigmaXL enables you to chart multiple Y responses.

Basic (Single) Pareto Charts

1. Open the file **Customer Data.xls**. Click SigmaXL > Graphical Tools > Basic Pareto Chart.

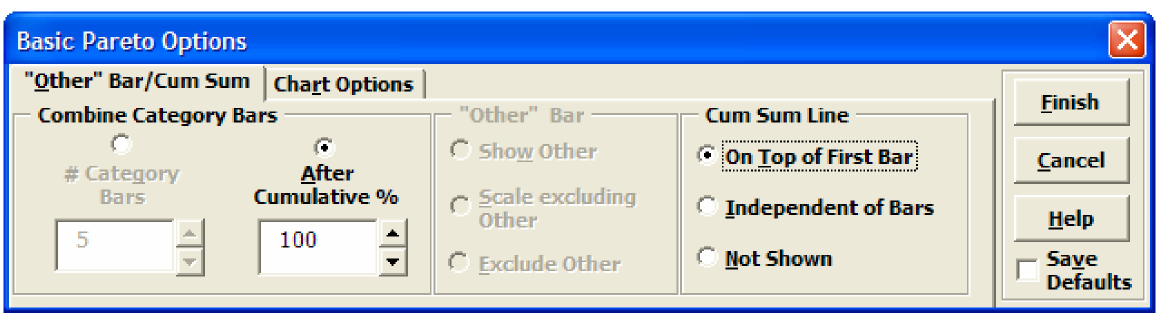
2. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

3. Select Major-Complaint as the Pareto Category (X).

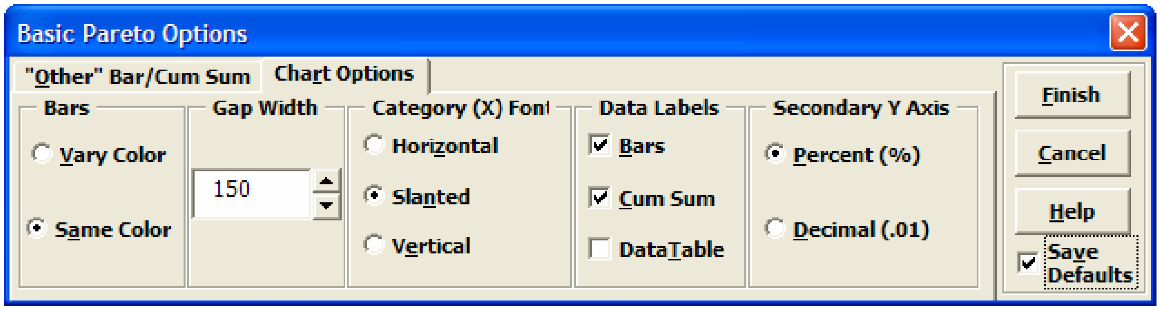


Tip: SigmaXL will automatically count the number of unique items in the Pareto Category. If we had a separate column with a count (or cost), this count column would be selected as the Optional Numeric Count (Y).

4. Click Next. Set Basic Chart Options as follows:
   Tab "Other" Bar/Cum Sum:
   Cum Sum Line – On Top of First Bar

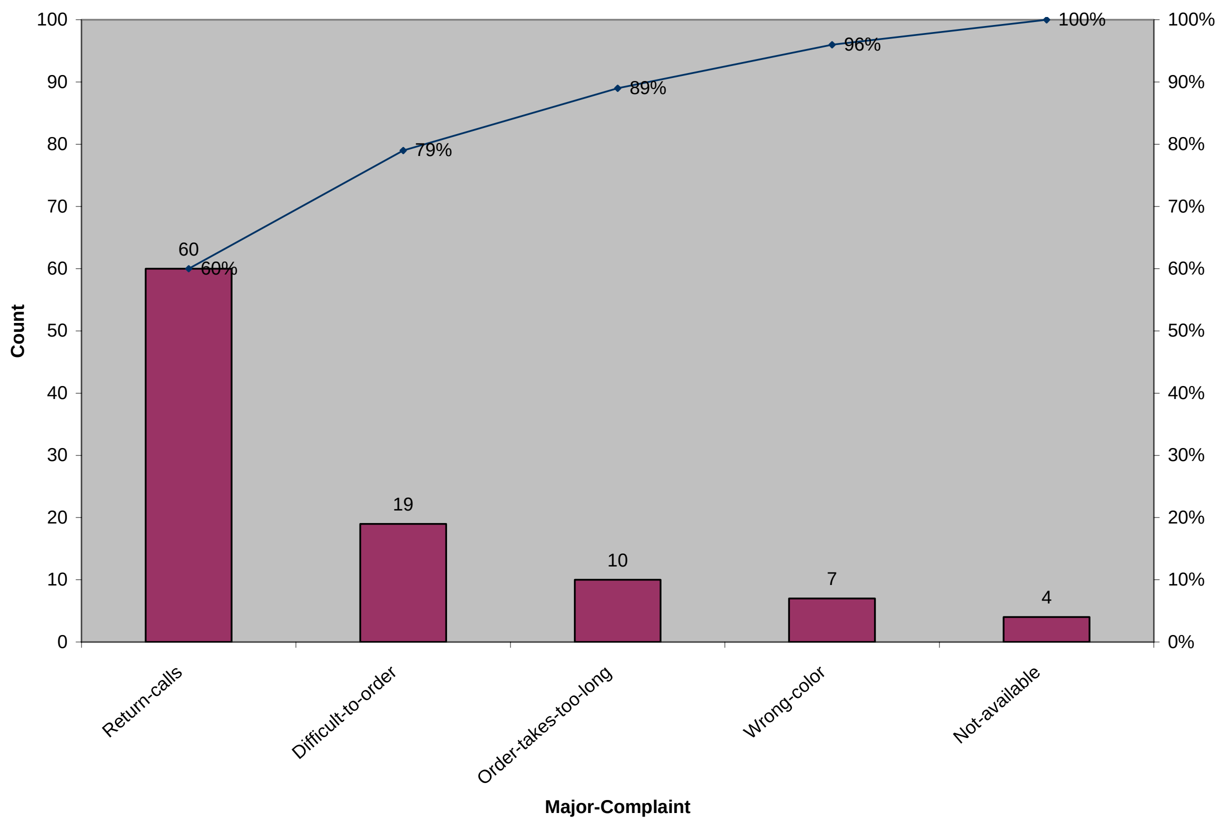


   Tab Chart Options
   Category (X) Font – Slanted
   Data Labels – Check Bars, Cum Sum
   Check Save Defaults



Tip: After you have saved your defaults, you can bypass the above options, by clicking "Finish" instead of "Next" at the original Basic Pareto Chart dialog box. The saved defaults will automatically be applied.

5. Click Finish. The Pareto Chart is produced:

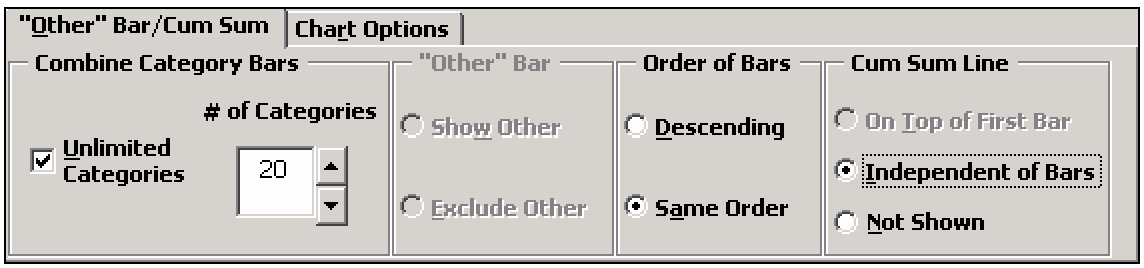


Advanced (Multiple) Pareto Charts

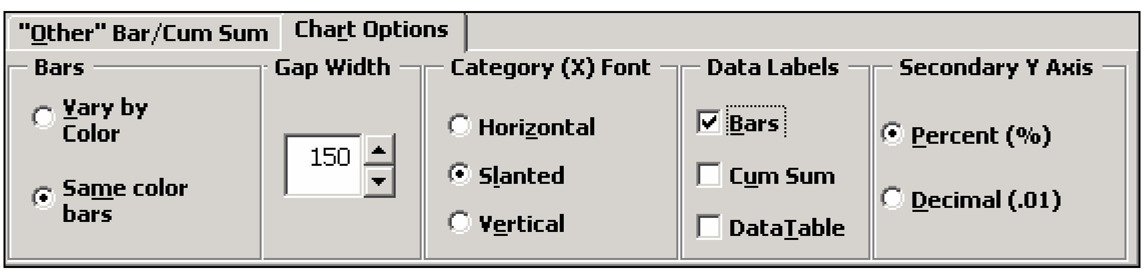
1. Click Sheet1 Tab of **Customer Data.xls** (or press **F4** to activate last worksheet).

2. Click SigmaXL > Graphical Tools > Advanced Pareto Options.
   Note that the Sample Charts have nothing to do with the data set being evaluated. They are used to dynamically illustrate how your options affect the charts to be produced.

3. Set Order of Bars to "Same Order" on the "Other Bar"/Cum Sum options tab.
   This is typically used for comparative purposes. The Descending Order option makes each Chart a true Pareto Chart, but is less useful for comparison.



4. Click Chart Options tab. Set according to choice – in this case we have selected Data Labels for the Bars but not for the Cum Sum line.

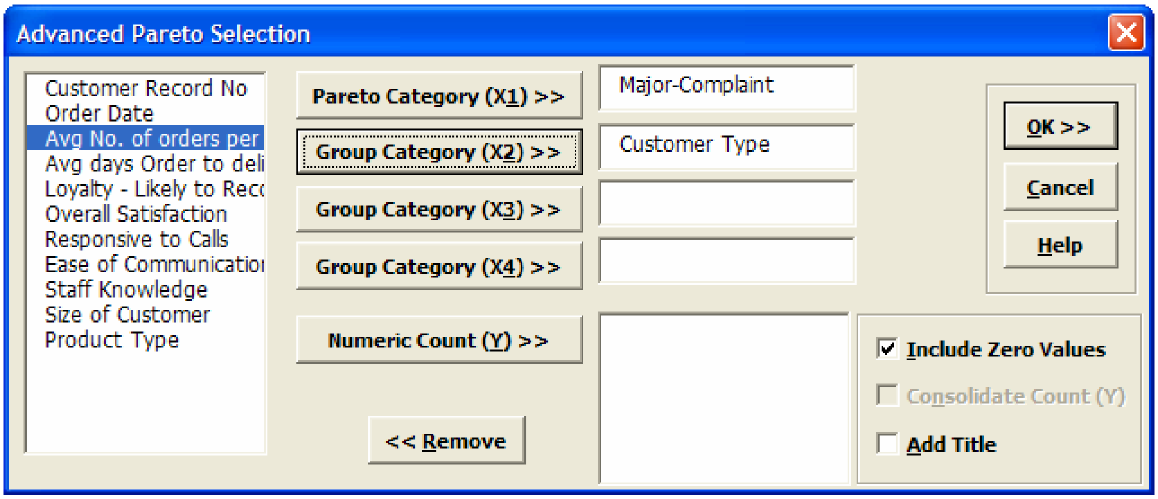


5. Ensure that Save Defaults is checked. Note that these options will be saved and applied to all Advanced Pareto Charts. Click Finish.

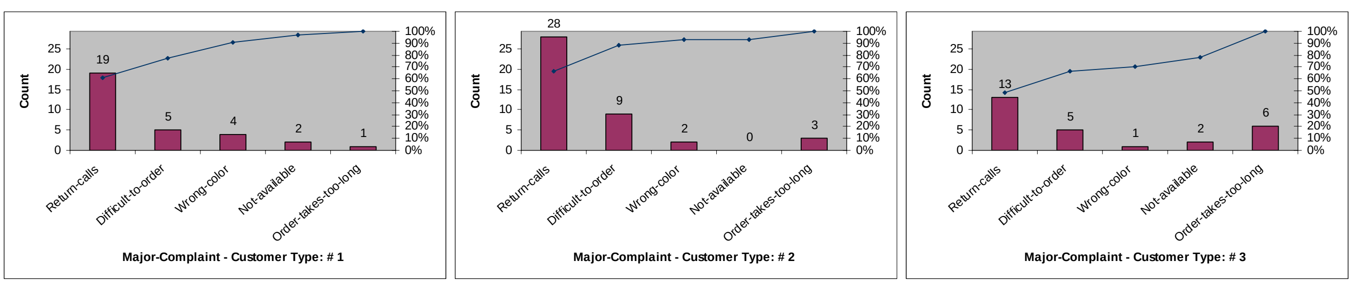
6. SigmaXL automatically takes you to the next step of Chart Generation (This is equivalent to clicking SigmaXL > Graphical Tools > Advanced Pareto Charts). If necessary, check "Use Entire Data Table"

7. Click Next.

8. Select Major Complaint as X1, Customer Type as X2.



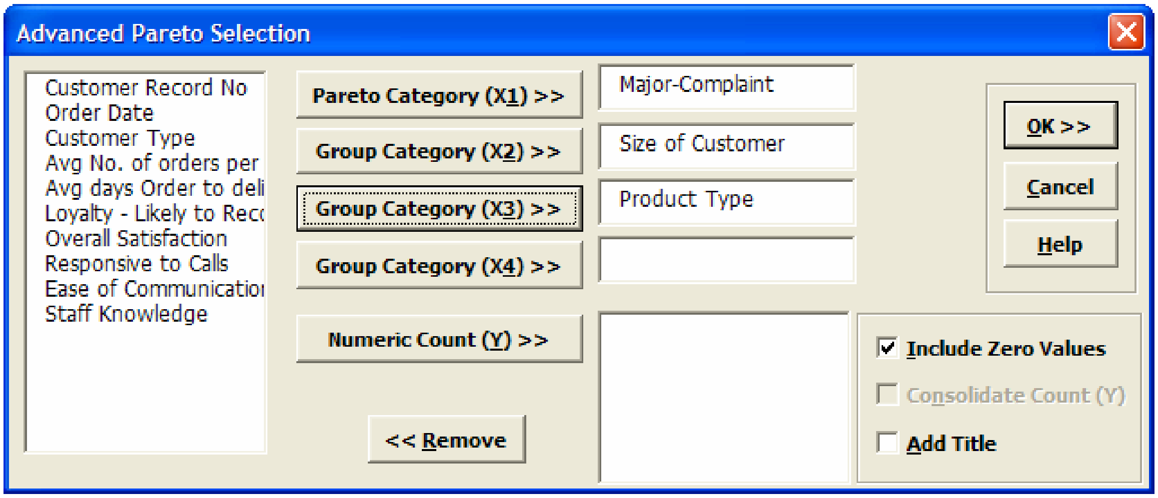
9. Click OK. A Pareto Chart of Major Customer Complaints is produced for each Customer Type.



10. Click Sheet 1 Tab, Click SigmaXL > Graphical Tools > Advanced Pareto Charts.

11. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next. (Steps 10 and 11 can be bypassed with the "Recall SigmaXL Dialog" menu or by pressing **F3** to recall last dialog).

12. Select Major Complaint as X1, Size of Customer as X2, and Product Type as X3.

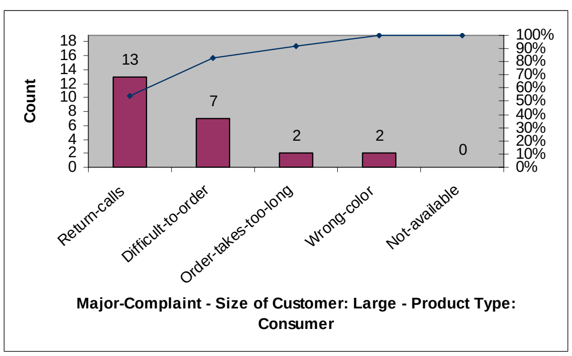


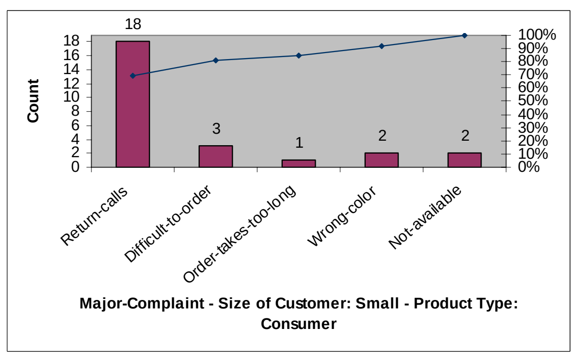
If a Numeric Count (Y) variable is not specified, SigmaXL automatically determines the counts from the Pareto Category (X1).

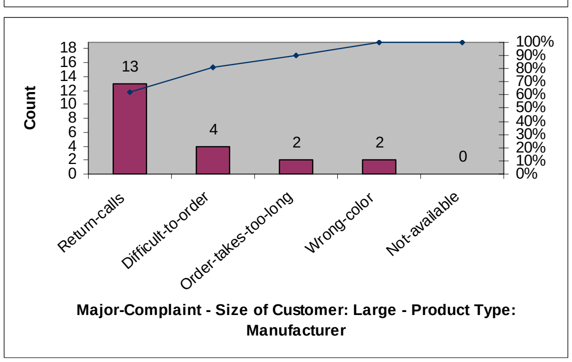
Normally we would use a text column of discrete Xs, but be aware that numeric columns are also allowed. **Be careful here – this could easily generate a very large number of charts.**

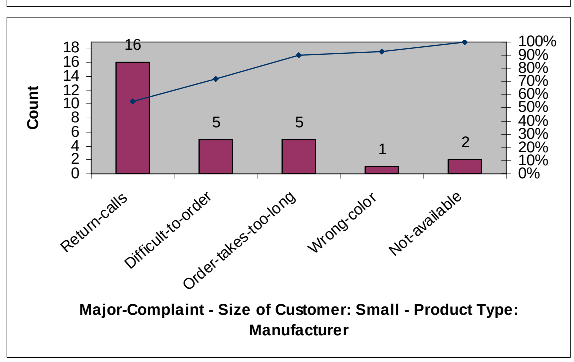
The total number of charts generated = (# of levels in X2) * (# of levels in X3) * (# of levels in X4) * (# of Y variables).

13. Click OK. Multiple Paretos are generated:









Part B - EZ-Pivot

One of the most powerful features in Excel is the Pivot table. However, this tool is often not used due to the non-intuitive nature of the interface. SigmaXL's EZ-Pivot tool simplifies the creation of Pivot tables using the familiar X and Y dialog box found in the previous Pareto tools.

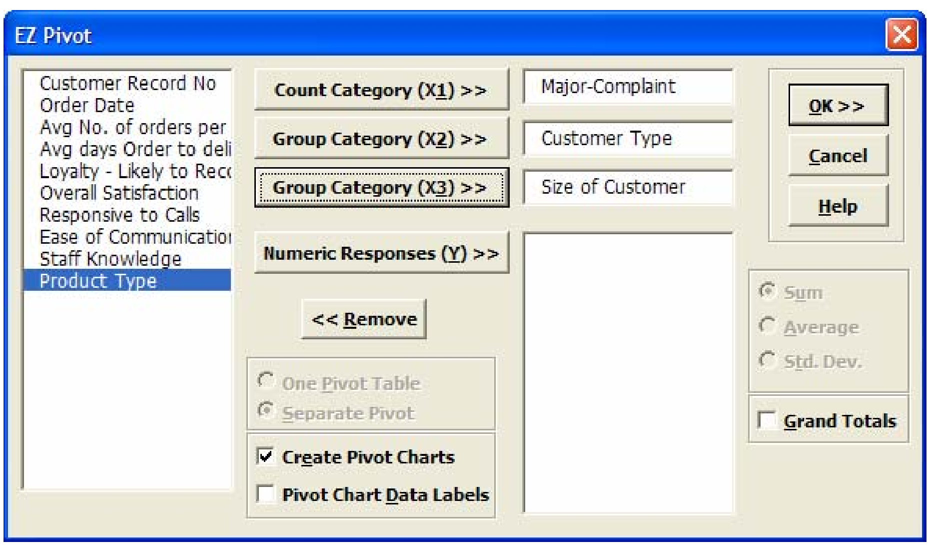
Example of Three X's, No Response Y's

1. Open **Customer Data.xls**, click Sheet 1 (or press **F4** to activate last worksheet). Select SigmaXL > click EZ-Pivot

2. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

3. Select Major Complaint as X1. Note that if Y is not specified, the Pivot Table Data is based on a count of X1, hence the name Count Category.

4. Select Customer Type as X2; Size of Customer as X3 as shown.

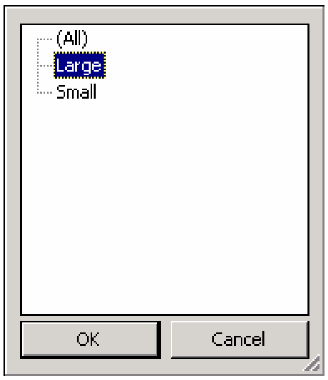


5. Click OK. Resulting Pivot Table of Major Complaint by Customer Type is shown:

Size of Customer	(All)		
Count of Major-Complaint	Customer Type		
Major-Complaint	1	2	3
Difficult-to-order	5	9	5
Not-available	2		2
Order-takes-too-long	1	3	6
Return-calls	19	28	13
Wrong-color	4	2	1

6. This Pivot table shows the counts for each Major Complaint (X1), broken out by Customer Type (X2), for all Sizes of Customers (X3). (Grand Totals can be added to the Pivot Table by using Pivot Table Toolbar > Table Options. Check Grand Totals for Columns, Grand Totals for Rows).

7. To display counts for a specific Customer Size, click the arrow adjacent to Size of Customer (All). Select Large.

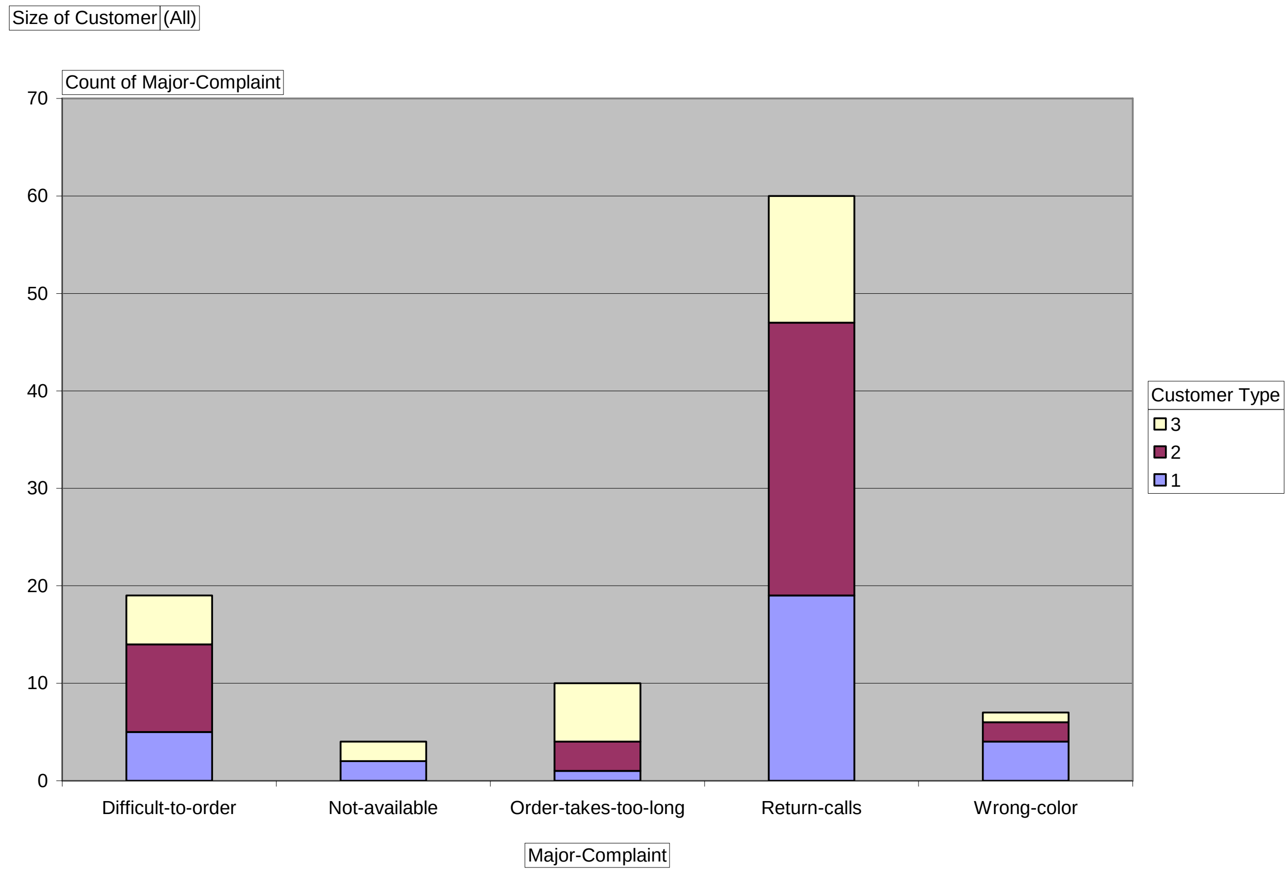


8. Click OK. Resulting Pivot Table is:

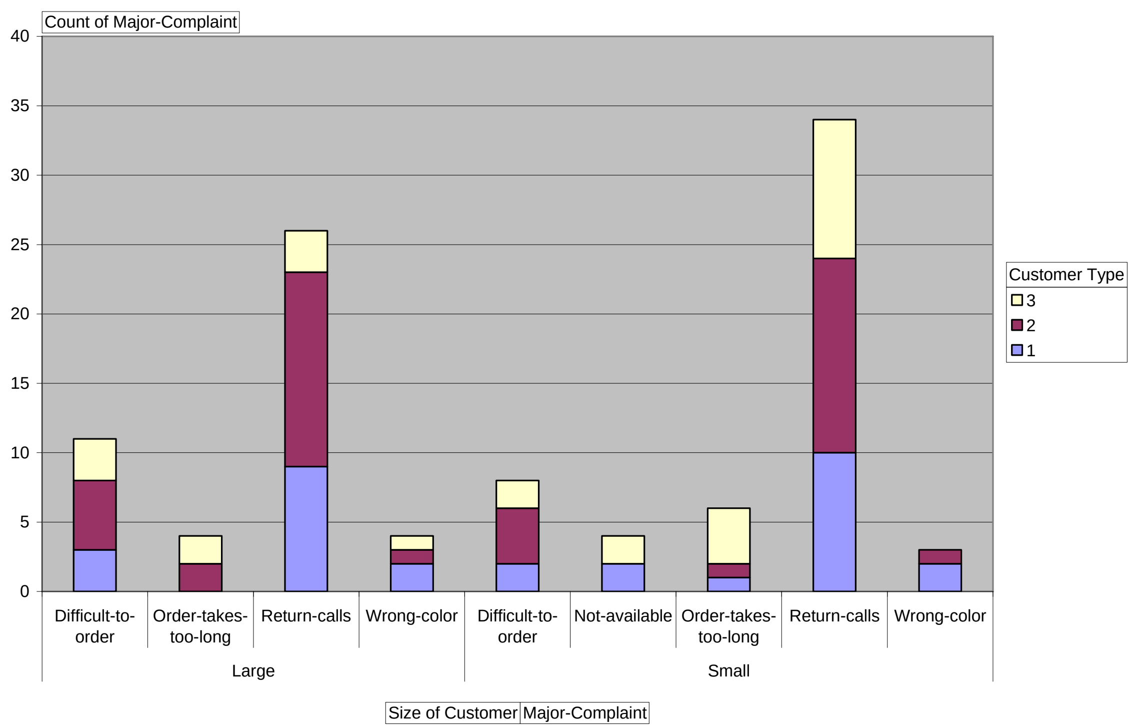
Size of Customer	Large		
Count of Major-Complaint	Customer Type		
Major-Complaint	1	2	3
Difficult-to-order	3	5	3
Order-takes-too-long		2	2
Return-calls	9	14	3
Wrong-color	2	1	1

Note that the Major Complaint "Not-Available" is not shown. Pivot table only show rows where there is at least a count of one.

9. The Pivot Chart can be seen by clicking the EZ Pivot Chart (1) tab; reset Size of Customer to All as shown below:



10. Drag the Size of Customer button adjacent to the left of the Major Complaint button and Excel will automatically split the Pivot Chart showing both Large and Small Customers.

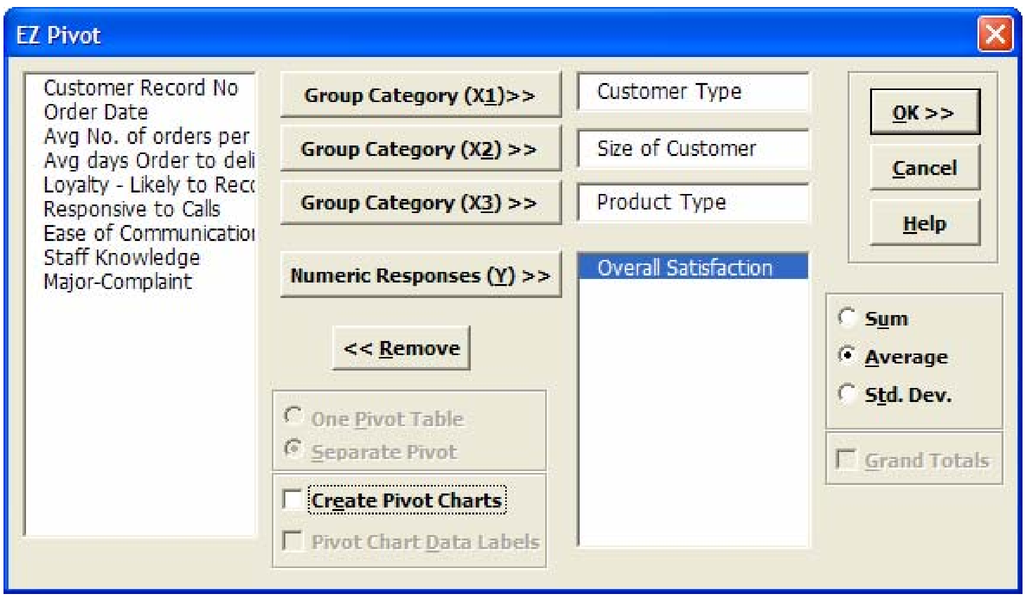


Example of Three X's and One Y

1. Select Sheet 1 **Customer Data.xls**; click SigmaXL > EZ-Pivot; click Next (alternatively, click "Recall SigmaXL Dialog" menu or press **F3** to recall last dialog).

2. Select Customer Type as X1; Size of Customer as X2; Product Type as X3; Overall Satisfaction as Y. Note that the Label for X1 changed from Count Category to Group Category. The Pivot Table data will now be based on Y data.

3. The Response default uses a Sum of Y. This however can be changed to Average or Standard Deviation. Select Average. Uncheck "Create Pivot Charts" (Since we are looking at averages, the stacked bar Pivot Charts would not be very useful, unless they are changed to "clustered column" format using Chart > Chart Type).



4. Click Ok. The resulting Pivot Table is:

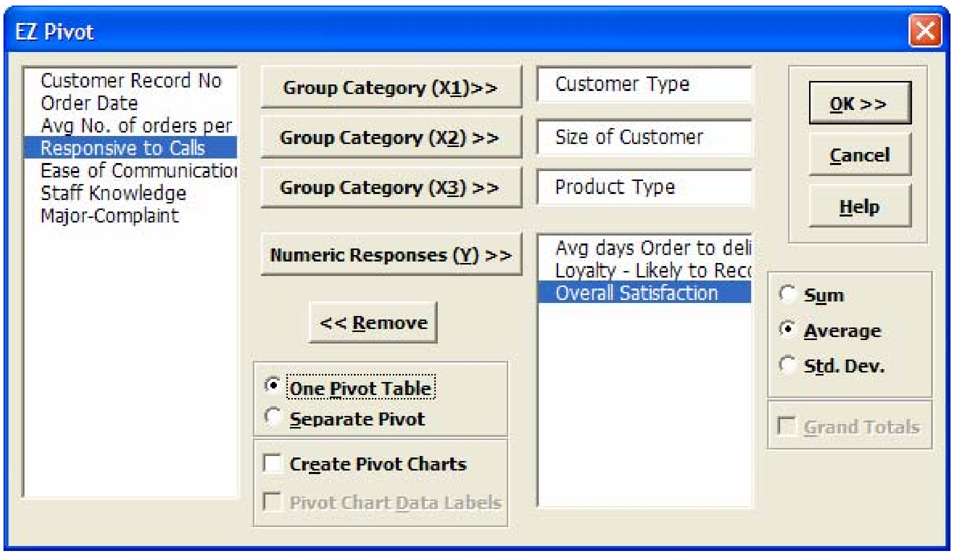
Product Type	(All)	
Average of Overall Satisfaction	Size of Customer	
Customer Type	Large	Small
1	3.237857143	3.521764706
2	4.309090909	4.091
3	3.56	3.681666667

5. Note that the table now contains Averages of the Customer Satisfaction scores (Y). Again Product Type (X3) can be varied to show Consumer, Manufacturer, or All. Double clicking on "Average of Overall Satisfaction" allows you to switch to Standard Deviation (StdDev).

Example of 3 X's and 3 Y's

1. Click "Recall SigmaXL Dialog" menu or press **F3** to recall last dialog.

2. Set X1=Customer Type; X2=Size of Customer; X3=Product Type; Y1=Avg Days Order to Delivery; Y2=Loyalty; Y3=Overall Satisfaction. Select Average and One Pivot Table (default is separate Pivot Tables for each Y). Uncheck "Create Pivot Charts".



3. Click OK. Resulting Pivot Table:

Product Type	(All)		
		Size of Customer	
Customer Type	Data	Large	Small
1	Average of Avg days Order to delivery time	50.85714286	49.76470588
	Average of Loyalty - Likely to Recommend	2.857142857	3.470588235
	Average of Overall Satisfaction	3.237857143	3.521764706
2	Average of Avg days Order to delivery time	48.63636364	49.65
	Average of Loyalty - Likely to Recommend	3.818181818	3.85
	Average of Overall Satisfaction	4.309090909	4.091
3	Average of Avg days Order to delivery time	47	47.66666667
	Average of Loyalty - Likely to Recommend	3.333333333	3.5
	Average of Overall Satisfaction	3.56	3.681666667

4. Again, Product Type (X3) can be varied.

Part C – Confidence Intervals

Confidence Intervals

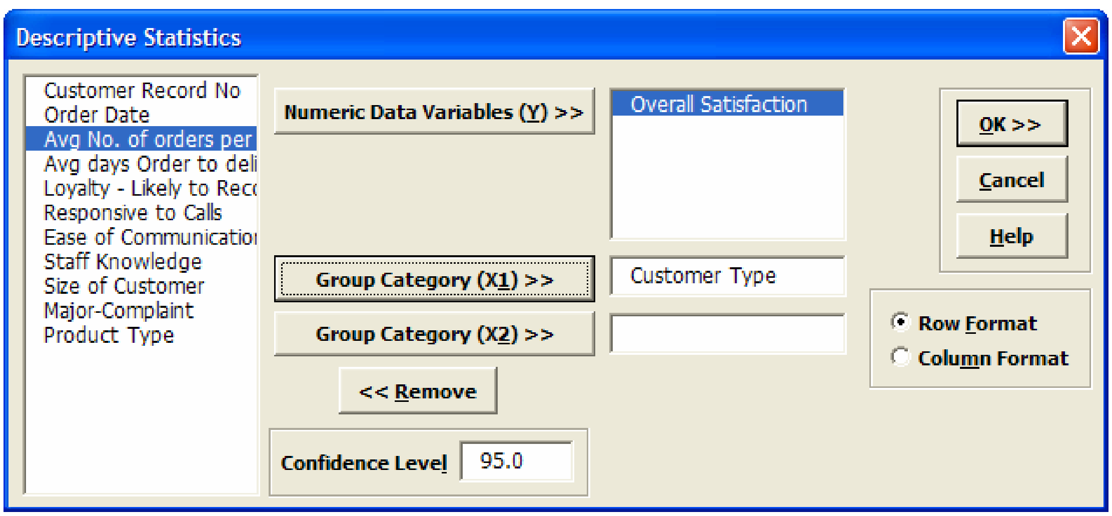
1. Confidence Intervals can be obtained in several ways with SigmaXL: Descriptive Statistics, Histograms & Descriptive Statistics, 1-Sample t-test and Confidence Intervals, One-Way ANOVA, and Multi-Vari Charts.

2. Open **Customer Data.xls.** Click Sheet 1 Tab (or press **F4** to activate last worksheet).

3. Click SigmaXL > Statistical Tools > Descriptive Statistics

4. Check "Use Entire Data Table", click Next

5. Select Overall Satisfaction, click Numeric Data Variables (Y) >>. Select Customer Type, click Group Category (X1) >>; Confidence level default is 95%:



6. Click OK. Descriptive Statistics are given for Customer Satisfaction broken out by Customer Type:

Overall Satisfaction by Customer Type			
	Customer Type = 1	Customer Type = 2	Customer Type = 3
Count	31	42	27
Mean	3.3935	4.2052	3.6411
Stdev	0.824680	0.621200	0.670478
Range	3.0800	2.5600	2.7400
Minimum	1.7200	2.4200	2.1900
25th Percentile (Q1)	2.8100	3.8275	3.2400
50th Percentile (Median)	3.5600	4.3400	3.5100
75th Percentile (Q3)	4.0200	4.7250	4.1700
Maximum	4.8000	4.9800	4.9300
95.0% CI Mean	3.091054 to 3.696043	4.011659 to 4.398818	3.375879 to 3.906344
95.0% CI Sigma	0.659012 to 1.102328	0.511126 to 0.792132	0.528013 to 0.918845
Anderson-Darling Normality Test	A-Squared = 0.312776; P-Value = 0.5306	A-Squared = 0.826259; P-Value = 0.0302	A-Squared = 0.389291; P-Value = 0.3600

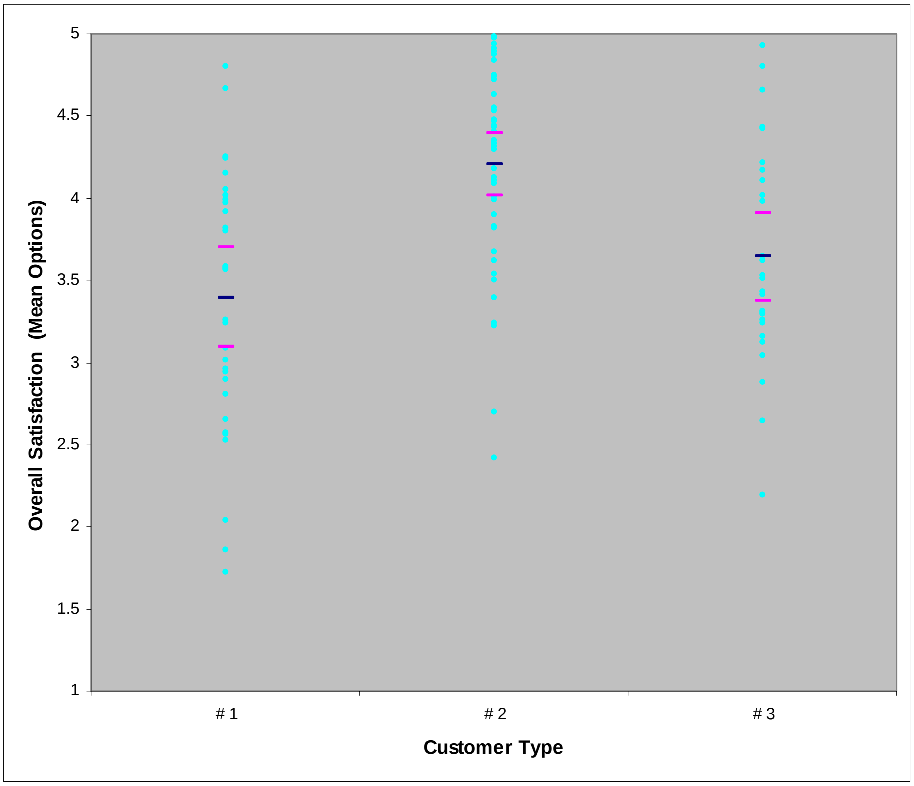
We are given the 95% confidence interval for each sample Mean (95% CI Mean) as well as the 95% confidence interval for the Standard Deviation (95% CI Sigma).

These confidence intervals are very important in understanding our data and making decisions from the data. How often are we driven by sample estimates only and fail to consider the confidence interval or margin of error? For example, newspapers will often fail to take into account the confidence interval when reporting opinion poll results. (To calculate confidence intervals for discrete data, use SigmaXL > Templates & Calculators > 1 Proportion Confidence Interval).

Note that a confidence interval of 95% implies that, on average, the true population parameter (Mean, Median, Sigma, or Proportion) will lie within the interval 19 times out of 20.

A confidence interval or margin of error does not take into account measurement error or survey bias, so the actual uncertainty may be greater than stated. This should be addressed with good data collection, reliable measurement systems, and good survey design.

To illustrate the confidence intervals graphically, we have generated a Multi-Vari Chart (with 95% CI Mean Options) using the Customer Data.xls data. This chart type will be covered later (Part O).

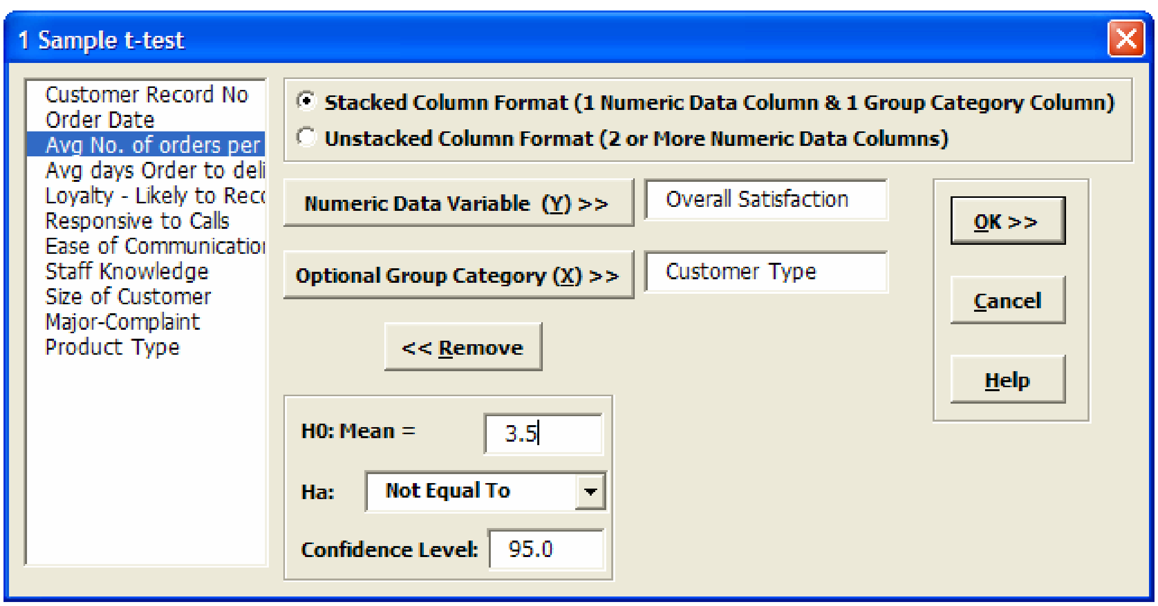


The dots correspond to individual data points. The tick marks show the 95% upper confidence limit, mean, and 95% lower confidence limit. Clearly we can see that Customer Type 2 has a significantly higher level of mean satisfaction; the lower limit does not overlap with the upper limit for Types 1 and 3. On the other hand we see overlap of the CI's when comparing types 1 and 3. Hypothesis testing will now be used to compare the mean satisfaction scores more precisely and determine statistical significance for the results.

Part D – Hypothesis Testing – One Sample t-Test

Hypothesis Testing – One Sample t-Test

1. Open **Customer Data.xls**, select Sheet 1 tab (or press **F4** to activate last worksheet). Click SigmaXL > Statistical Tools > 1 Sample t-Test & Confidence Intervals. If necessary, check Use Entire Data Table, click Next.
2. Ensure that "Stacked Column Format" is selected. Select Overall Satisfaction as Numeric Data Variable (Y), Customer Type as Optional Group Category (X).
3. Historically, our average customer satisfaction score has been 3.5. We would like to see if this has changed, with the results grouped by customer type. Null Hypothesis H0: μ=3.5; Alternative Hypothesis Ha: μ≠3.5
4. Enter 3.5 for the Null Hypothesis H0 value. Keep Ha as "Not Equal To".



5. Click OK. Results:

1 Sample t-test - Overall Satisfaction			
H0: Mean (Mu) = 3.5			
Ha: Mean (Mu) Not Equal To 3.5			
Customer Type	1	2	3
Count	31	42	27
Mean	3.3935	4.2052	3.6411
StDev	0.824680	0.621200	0.670478
SE Mean	0.148117	0.095853	0.129034
t	-0.718700	7.3575	1.0936
p-value (2-sided)	0.4779	0.0000	0.2842
UC (2-sided, 95%)	3.6960	4.3988	3.9063
LC (2-sided, 95%)	3.0911	4.0117	3.3759

6. Note the p-values. Customer Type 2 shows a significant change (increase) in Satisfaction Mean (p-value < .05), whereas Customer Types 1 and 3 show no change (p-value ≥ .05). Also note the confidence intervals around each mean match the results from Descriptive Statistics.

7. In the Measure Phase we determined that Overall Satisfaction for Customer Type 2 has non-normal data but this does not imply that the p-value for the 1 Sample t-test is wrong. The Central Limit Theorem applies here: the distribution of averages tends to be normal, even if the individual observations are not-normal. With a sample size of 42, the t-test is fairly robust against skewed data.

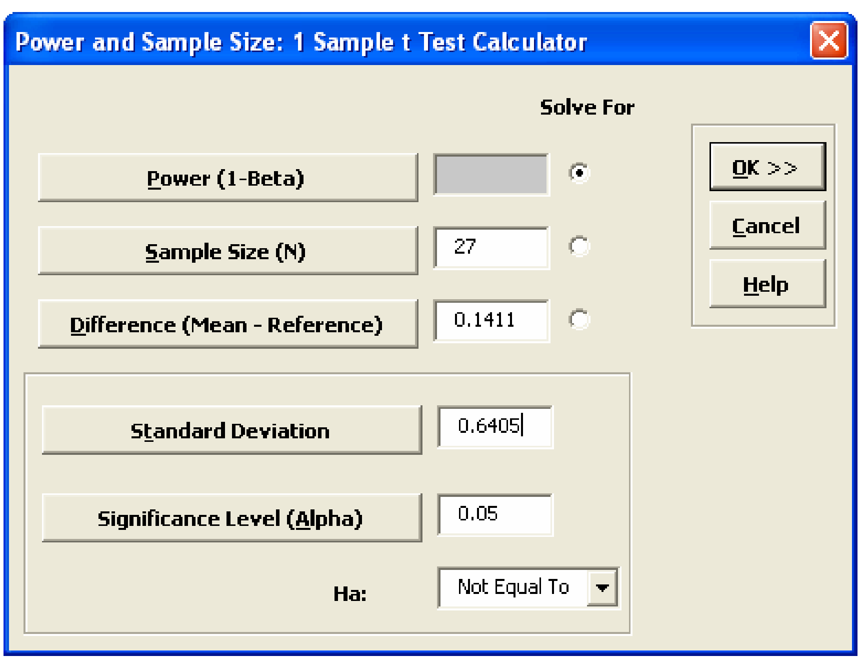
Part E – Power and Sample Size

Power and Sample Size – One Sample t-Test – Customer Data

Using the One Sample t-Test, we determined that Customer Types 1 and 3 resulted in "Fail to reject H0: μ=3.5". A failure to reject H0 does not mean that we have proven the null to be true. The question that we want to consider here is "What was the power of the test?" Restated, "What was the likelihood that given Ha: μ≠3.5 was true, we would have rejected H0 and accepted Ha?" To answer this, we will use the Power and Sample Size Calculator.

1. Click SigmaXL > Statistical Tools > Power and Sample Size Calculators > 1 Sample t-Test Calculator. We will only consider the statistics from Customer Type 3 here. We will treat the problem as a two sided test with Ha: "Not Equal To" to be consistent with the original test.

2. Enter 27 in Sample Size (N). The difference to be detected in this case would be the difference between the sample mean and the hypothesized value i.e. 3.6411 – 3.5 = 0.1411. Enter 0.1411 in Difference. Leave Power value blank, with "Solve For" Power selected (default). Given any two values of Power, Sample size, and Difference, SigmaXL will solve for the remaining selected third value. Enter the sample standard deviation value of 0.6405 in Standard Deviation. Keep Alpha and Ha at the default values as shown:

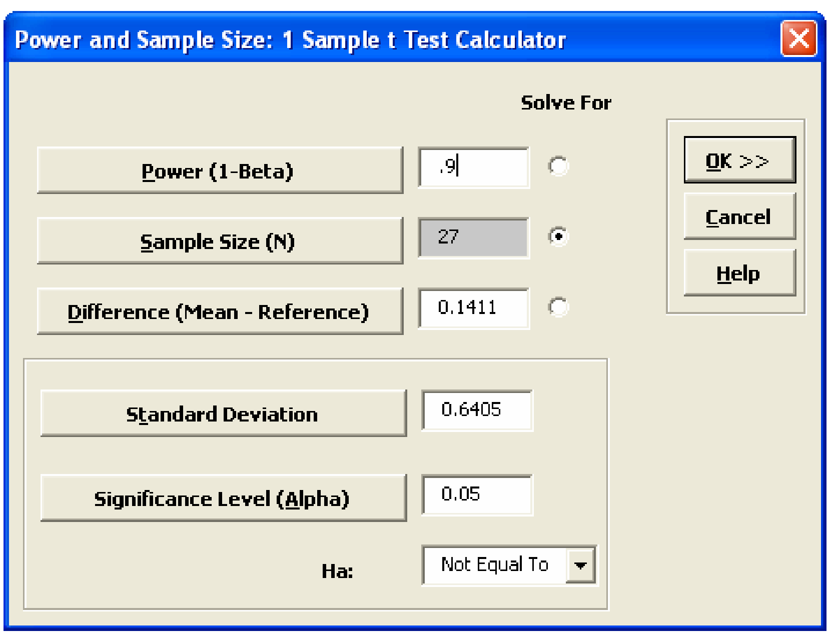


3. Click OK. The resulting report is shown:

Power and Sample Size: 1 Sample t Test				
H0: Mean (μ) = Reference				
Ha: Mean (μ) ≠ Reference				
Solve For: Power (1 - Beta)				
Sample Size (N)	**Difference**	**Standard Deviation**	**Significance Level (Alpha)**	**Power (1 - Beta)**
27	0.1411	0.6405	0.05	0.19675444

4. A power value of 0.1968 is very poor. It is the probability of detecting the specified difference. Alternatively, the associated Beta risk is 1-0.1968 = 0.8032 which is the probability of failure to detect such a difference. Typically, we would like to see Power > 0.9 or Beta < 0.1. In order to detect a difference this small we would need to increase the sample size. We could also set the difference to be detected as a larger value.

5. First we will determine what sample size would be required in order to obtain a Power value of 0.9. Click "Recall SigmaXL Dialog" menu or press **F3** to recall last dialog. Select the "Solve For" Sample Size button as shown. It is not necessary to delete the entered sample size of 27 – it will be ignored. Enter a Power Value of .9:

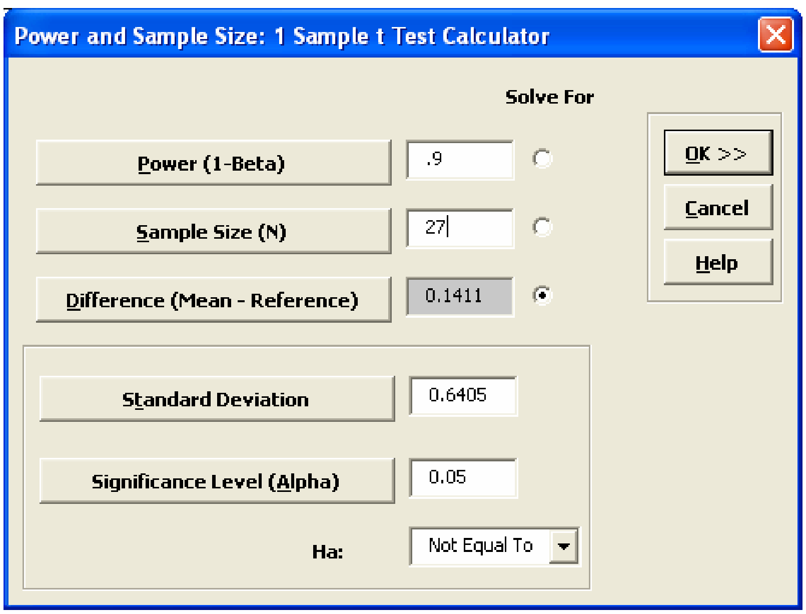


6. Click OK. The resulting report is shown:

Power and Sample Size: 1 Sample t Test					
H0: Mean (µ) = Reference					
Ha: Mean (µ) ≠ Reference					
Solve For: Sample Size (N)					
Power (1 - Beta)	**Difference**	**Standard Deviation**	**Significance Level (Alpha)**	**Sample Size (N)**	**Actual Power**
0.9	0.1411	0.6405	0.05	219	0.900732021

7. A sample size of 219 would be required to obtain a power value of 0.9. The actual power is rarely the same as the desired power due to the restriction that the sample size must be an integer. The actual power will always be greater than or equal to the desired power.

8. Now we will determine what the difference would have to be to obtain a Power value of 0.9, given the original sample size of 27. Click "Recall SigmaXL Dialog" menu or press **F3** to recall last dialog. Select the "Solve For" Difference button as shown:



9. Click OK. The resulting report is shown:

Power and Sample Size: 1 Sample t Test				
H0: Mean (µ) = Reference				
Ha: Mean (µ) ≠ Reference				
Solve For: Difference (Mean - Reference)				
Power (1 - Beta)	**Sample Size (N)**	**Standard Deviation**	**Significance Level (Alpha)**	**Difference**
0.9	27	0.6405	0.05	0.4151905

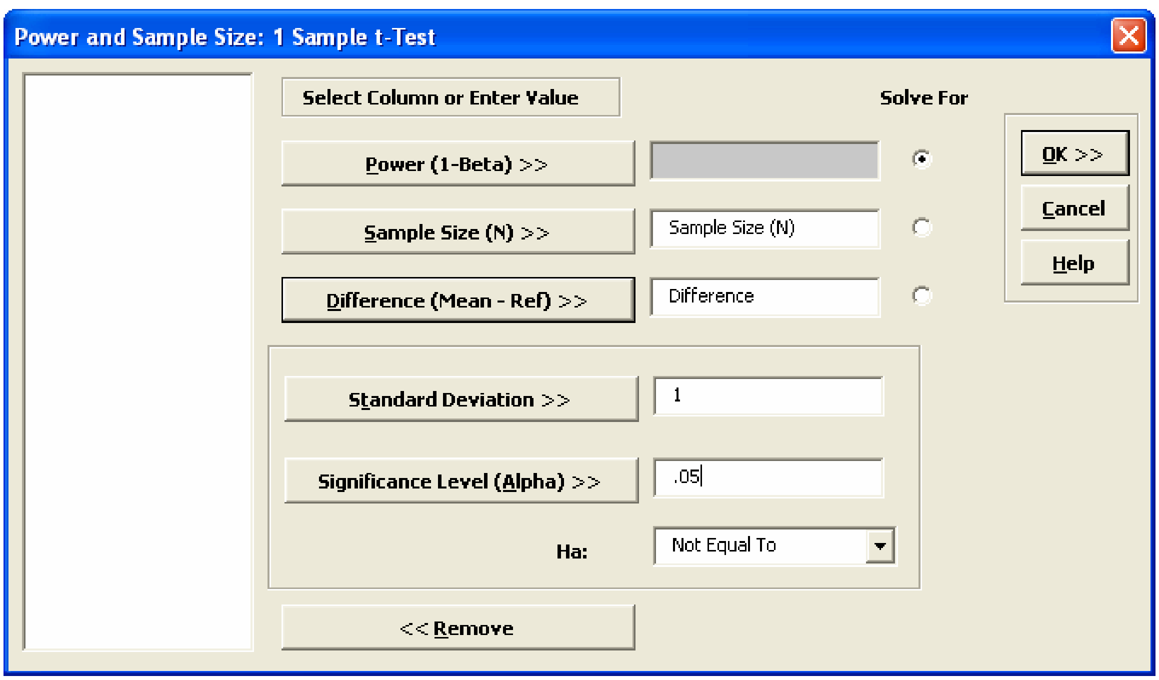
10. A difference of 0.415 would be required to obtain a Power value of 0.9, given the sample size of 27.

Power and Sample Size – One Sample t-Test – Graphing the Relationships between Power, Sample Size, and Difference

In order to provide a graphical view of the relationship between Power, Sample Size, and Difference, SigmaXL provides a tool called **Power and Sample Size with Worksheets**. Similar to the Calculators, **Power and Sample Size with Worksheets** allows you to solve for Power (1 – Beta), Sample Size, or Difference (specify two, solve for the third). You must have a worksheet with Power, Sample Size, or Difference values. Other inputs such as Standard Deviation and Alpha can be included in the worksheet or manually entered.

1. Open the file **Sample Size and Difference Worksheet.xls**, select the **Sample Size & Diff** sheet tab. Click SigmaXL > Statistical Tools > Power & Sample Size with Worksheets > 1 Sample t-Test. If necessary, check "Use Entire Data Table". Click Next.

2. Ensure that "Solve For" Power (1 – Beta) is selected. Select Sample Size (N) and Difference columns as shown. Enter the Standard Deviation value of 1. Enter .05 as the Significance Level value:



3. Click OK. The output report is shown below:

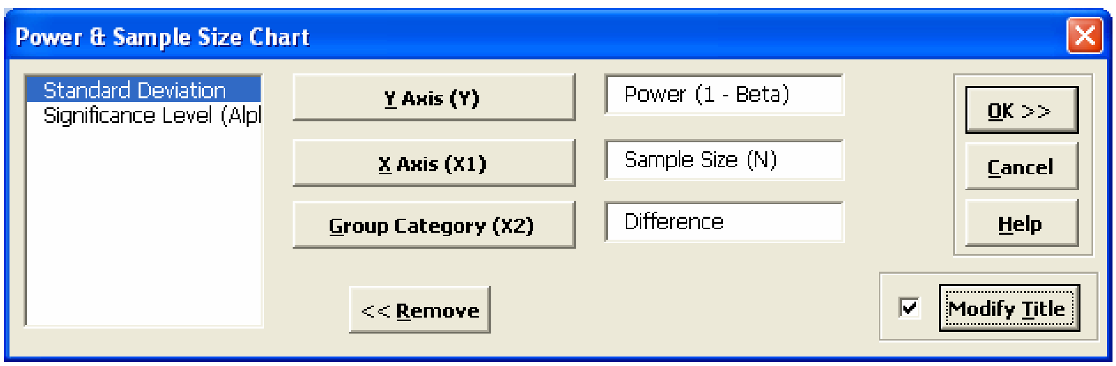
Power and Sample Size: 1 Sample t Test

H0: Mean (μ) = Reference
Ha: Mean (μ) ≠ Reference
Solve For: Power (1 - Beta)

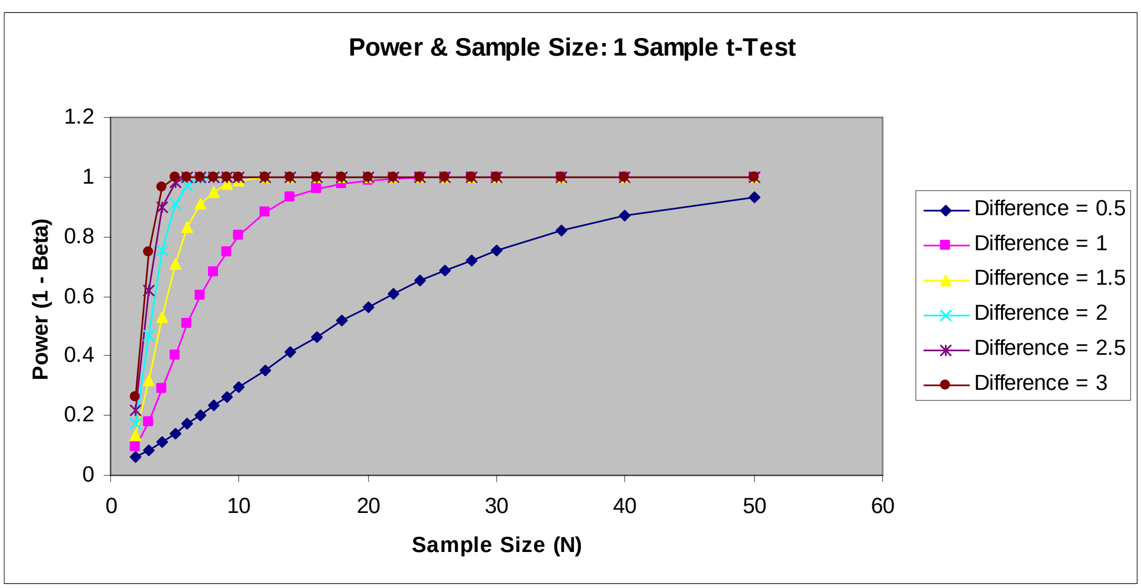
Sample Size (N)	Difference	Standard Deviation	Significance Level (Alpha)	Power (1 - Beta)
2	0.5	1	0.05	0.061948607
3	0.5	1	0.05	0.084107056
4	0.5	1	0.05	0.111274916
5	0.5	1	0.05	0.140516692
6	0.5	1	0.05	0.17070708
7	0.5	1	0.05	0.201327803
8	0.5	1	0.05	0.232077006
9	0.5	1	0.05	0.262746095
10	0.5	1	0.05	0.293175607

4. To create a graph showing the relationship between Power, Sample Size and Difference, click SigmaXL > Statistical Tools > Power & Sample Size Chart. Check "Use Entire Data Table". Click Next.

5. Select Power (1 – Beta) for the Y Axis, Sample Size (N) for the X axis, and Difference as the Group Category variable. Click Add Title. Enter "Power & Sample Size: 1 Sample t-Test":



6. Click OK. The resulting Power & Sample Size Chart is displayed:



Part F – One Sample Nonparametric Tests

Introduction to Nonparametric Tests

Nonparametric tests make fewer assumptions about the distribution of the data compared to parametric tests like the t-Test. Nonparametric tests do not rely on the estimation of parameters such as the mean or the standard deviation. They are sometimes called distribution-free tests.

Nonparametric tests use Medians and Ranks, thus they are robust to outliers in the data. If, however, the data are normal and free of outliers, nonparametric tests are less powerful than normal based tests to detect a real difference when one exists.

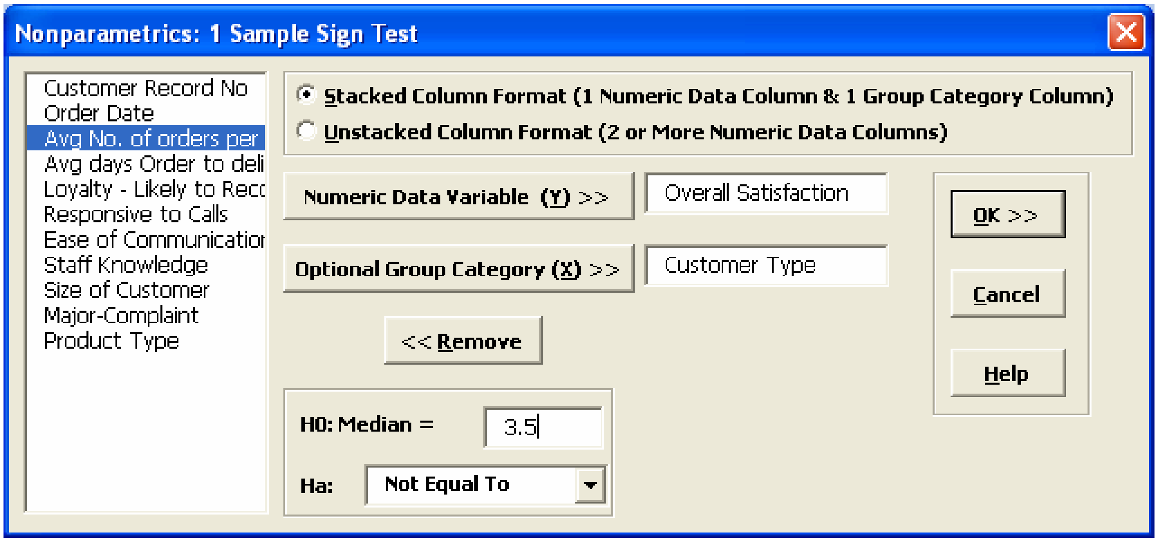
Nonparametric tests should be used when the data are non-normal, data cannot be readily transformed to normality, and sample size is small ($n < 30$). If the sample sizes are large, the Central Limit Theorem says that parametric tests are robust to non-normality.

One Sample Sign Test

The sign test is the simplest of the nonparametric tests, and is similar to testing if a two-sided coin is fair. Count the number of positive values (larger than hypothesized median), the number of negative values (smaller than the hypothesized median), and test whether there are significantly more positives (or negatives) than expected. The One Sample Sign Test is a nonparametric equivalent to the parametric One Sample t-Test.

Historically, our Median customer satisfaction score has been 3.5. We would like to see if this has changed, with the results grouped by customer type (H0: Median=3.5, Ha: Median≠3.5, $\alpha = 0.05$).

1. Open **Customer Data.xls**, select Sheet 1 tab. Click SigmaXL > Statistical Tools > Nonparametric Tests > 1 Sample Sign. If necessary, check “Use Entire Data Table”, click Next.
2. Ensure that “Stacked Column Format” is selected. Select Overall Satisfaction as Numeric Data Variable (Y), Customer Type as Optional Group Category (X).
3. Enter 3.5 for the Null Hypothesis H0 value. Set Ha as “Not Equal To”.



4. Click OK. Results:

1 Sample Sign Test for Medians: Overall Satisfaction			
H0: Median = 3.5			
Ha: Median Not Equal To 3.5			
Customer Type	1	2	3
Count (N)	31	42	27
Median	3.56	4.34	3.51
Points Below 3.5	15	5	13
Points Equal To 3.5	0	1	0
Points Above 3.5	16	36	14
p-value (2-sided)	1.0000	0.0000	1.0000

Note the p-values. Customer Type 2 shows a significant change (increase) in Satisfaction Median (p-value < .05), whereas Customer Types 1 and 3 show no change (p-value ≥ .05). While the p-values are not the same as those given by the 1 sample t-Test, the conclusions do match.

One Sample Wilcoxon Signed Rank Test

The Wilcoxon Signed Rank test is a more powerful nonparametric test than the Sign Test, but it adds an assumption that the distribution of values is symmetric around the median. An example of a symmetric distribution is the uniform distribution. Symmetry can be observed with a histogram, or by checking to see if the median and mean are approximately equal.

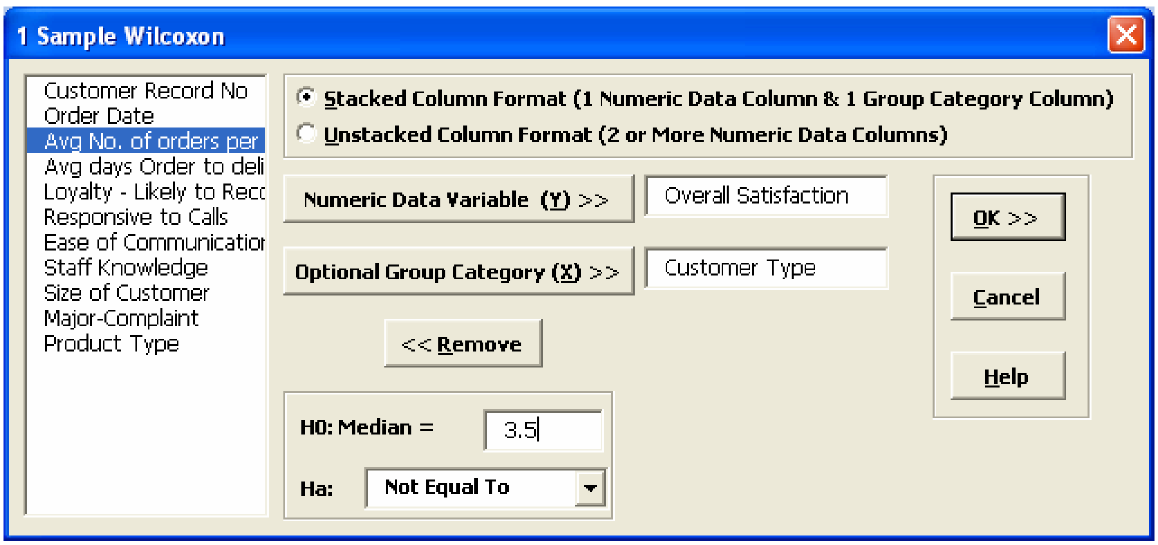
The One Sample Wilcoxon Test is a nonparametric equivalent to the parametric One Sample t-Test.

Historically, our Median customer satisfaction score has been 3.5. We would like to see if this has changed, with the results grouped by customer type (H0: Median=3.5, Ha: Median≠3.5, α = 0.05).

1. Open **Customer Data.xls**, select Sheet 1 tab (or press **F4** to activate last worksheet). Click SigmaXL > Statistical Tools > Nonparametric Tests > 1 Sample Wilcoxon. If necessary, check "Use Entire Data Table", click Next.

2. Ensure that "Stacked Column Format" is selected. Select Overall Satisfaction as Numeric Data Variable (Y), Customer Type as Optional Group Category (X).

3. Enter 3.5 for the Null Hypothesis H0 value. Keep Ha as "Not Equal To".



4. Click OK. Results:

1 Sample Wilcoxon Test: Overall Satisfaction			
H0: Median = 3.5			
Ha: Median Not Equal To 3.5			
Customer Type	1	2	3
Count (N)	31	42	27
Count for Test	31	41	27
Median	3.56	4.34	3.51
Wilcoxon Statistic	217.50	802.50	222.00
p-value (2-sided)	0.5566	0.0000	0.4349

Note the p-values. Customer Type 2 shows a significant change (increase) in Satisfaction Median (p-value < .05), whereas Customer Types 1 and 3 show no change (p-value ≥ .05). Although the p-values are not identical to the sign test and t-Test, the conclusions match. (Note, in the case of Customer Type 2, the Sign Test is preferred since the data is not symmetrical but skewed).

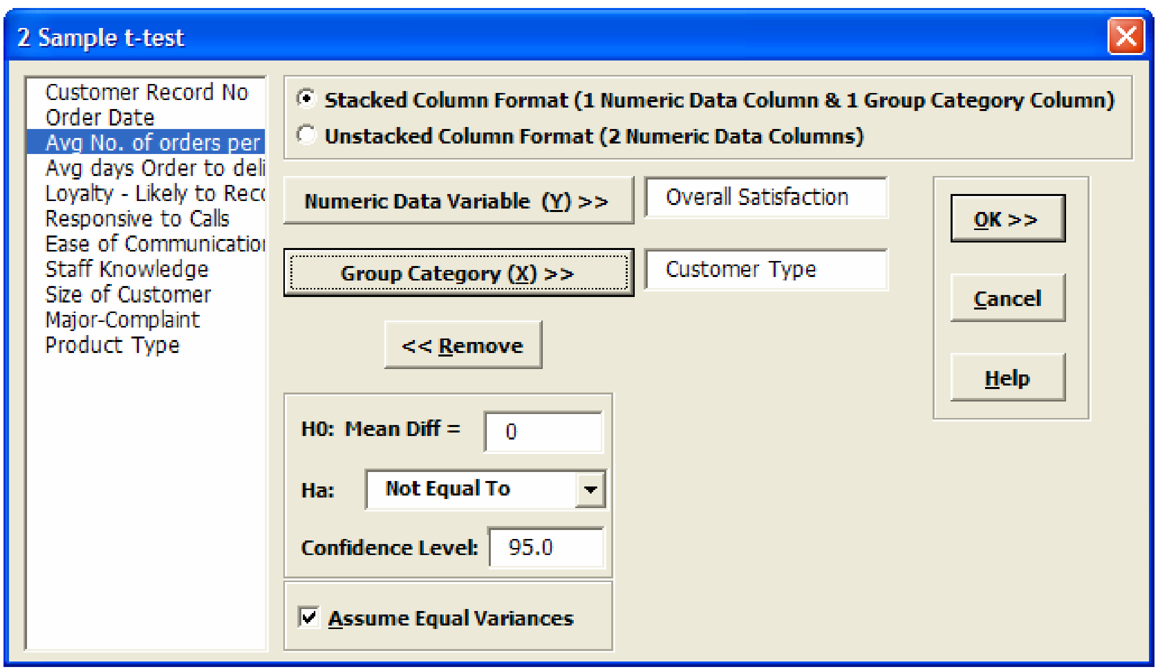
Part G – Two Sample t-Test

Two Sample t-Test

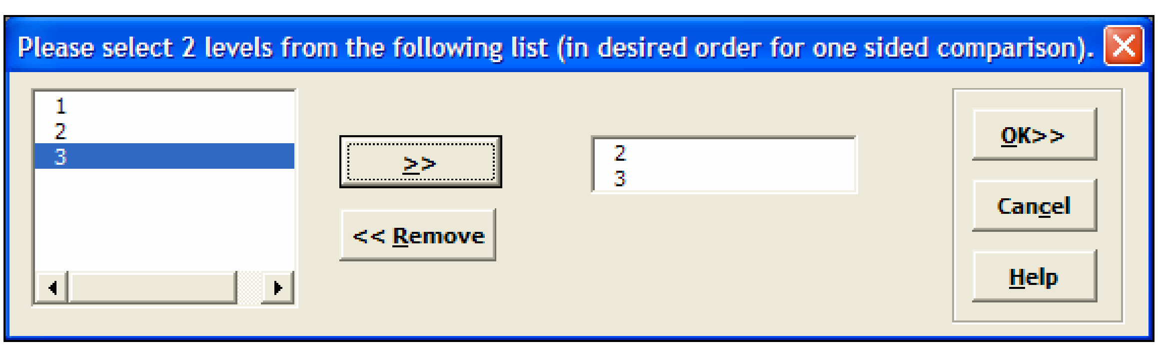
1. Open **Customer Data.xls**, click Sheet 1 tab (or press **F4** to activate last worksheet). We will look at comparing means of Customer Satisfaction by Customer Type (2 vs. 3), using the Two Sample t-test. H0: μ2=μ3, Ha: μ2≠μ3

2. Click SigmaXL > Statistical Tools > 2 Sample t-test. If necessary, check Use Entire Data Table, click Next.

3. With stacked column format checked, select Overall Satisfaction as Numeric Data Variable Y; Customer Type as Group Category X; H0: Mean Diff = 0; Ha: "Not Equal To"; Confidence Level: 95%; ensure that "Assume Equal Variances" is checked:



4. Click OK. Select Customer Type 2 and 3.



5. Click OK. Resulting output:

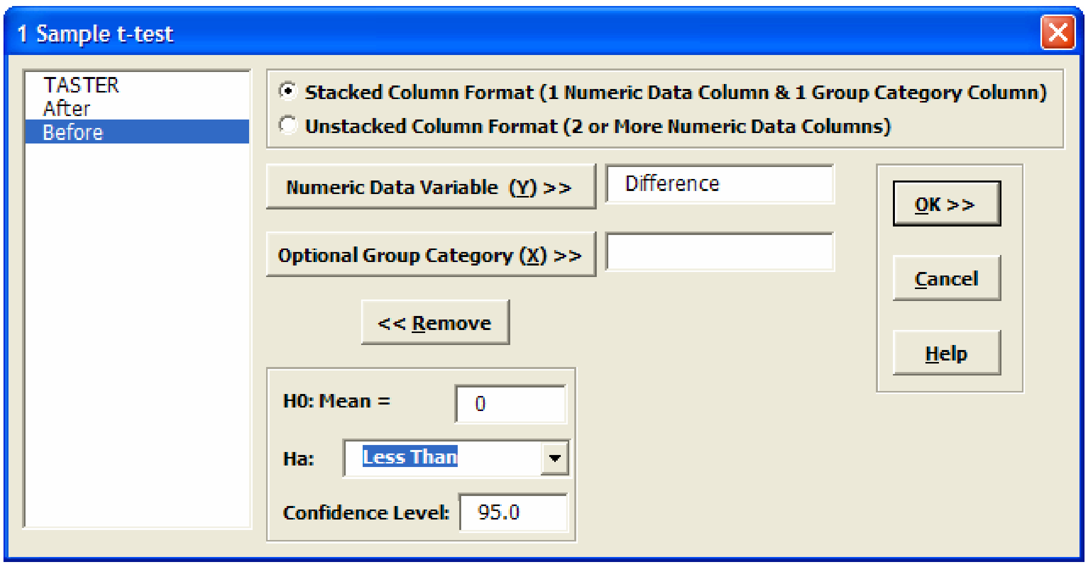
2 Sample t-test - Overall Satisfaction		
H0: Mean Difference = 0		
Ha: Mean Difference Not Equal To 0		
Assume Equal Variance		
Customer Type	2	3
Count	42	27
Mean	4.2052	3.6411
Standard Deviation	0.621200	0.670478
Mean Difference	0.564127	
Std Error Difference	0.158060	
DF	67	
t	3.5691	
p-value two-sided	0.0007	
UC (2-sided, 95%)	0.879616	
LC (2-sided, 95%)	0.248638	

Given the p-value of .0007 we reject H0 and conclude that Mean Customer Satisfaction is significantly different between Customer type 2 and 3. This confirms previous findings.

Paired t-Test

1. Open the file **Dietcola.xls**. These are the results of a Before and After taste test on sweetness for diet cola. Ten tasters were used and one month elapsed with the cola in warm storage between the before and after results. Do a one sample t-test on the column of differences.

2. Click SigmaXL > Statistical Tools > 1-Sample t-test & Confidence Intervals. Ensure that entire data table is selected. If not, check “Use Entire Data Table”. Click Next, Select Difference as Y, set H0: Mean μ=0, Ha: Less Than (this is a one-sided or one-tail test – sweetness cannot increase):

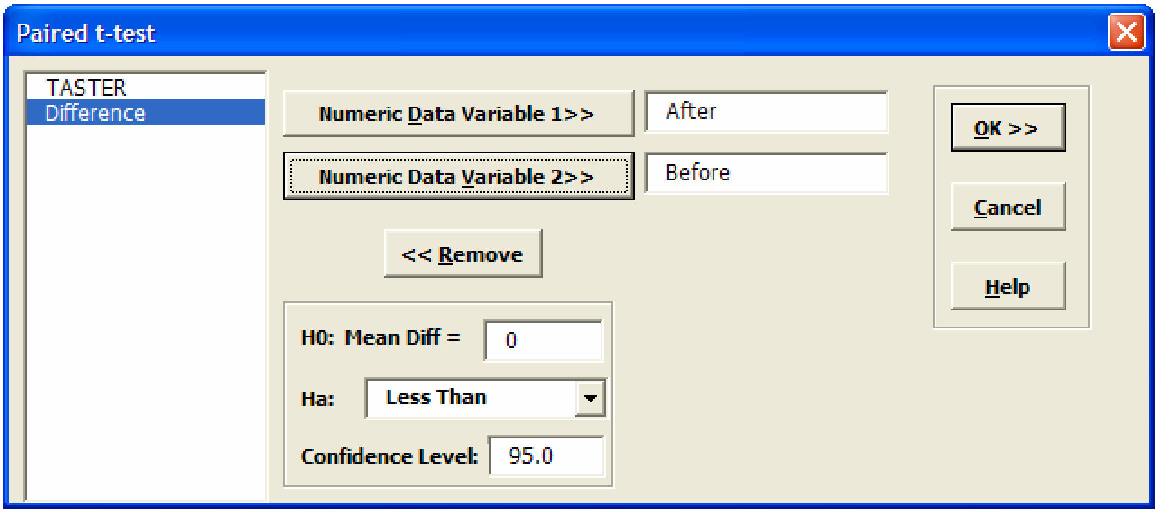


3. Click OK. Result:

1-Sample t-test	
H0: Mean (Mu) = 0	
Ha: Mean (Mu) Less Than 0	
	Difference
Count	10
Mean	-1.02
StDev	1.1961
SE Mean	0.378242
t	-2.6967
p-value (1-sided)	0.0123
UC (1-sided, 95%)	-0.326640

Given the p-value of .012, we reject H0 and conclude that the sweetness has in fact decreased.

4. Now redo the analysis using the paired t-test: Click Sheet 1 Tab; Click SigmaXL > Statistical Tools > Paired t-Test; Click Next; Select After as Data Variable 1, Before as Data Variable 2, H0: Mean Diff = 0, Ha: "Less Than"



5. Click OK. Results are identical to One sample analysis of difference column:

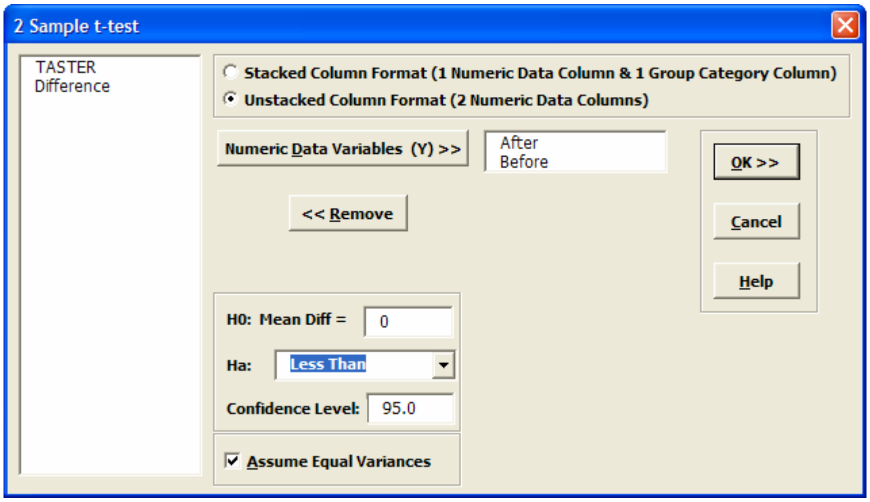
Paired t-test	
H0: Mean Difference = 0	
Ha: Mean Difference Less Than 0	
	After - Before
Count	10
Mean	-1.02
StDev	1.1961
SE Mean	0.378242
t	-2.6967
p-value (1-sided)	0.0123
UC (1-sided, 95%)	-0.326640

Unpaired 2 Sample t-Test vs. Paired t-Test

1. Open the **Dietcola.xls** file, click the Sheet 1 tab (or press **F4** to activate last worksheet).

2. Click SigmaXL > Statistical Tools > 2 Sample t-test. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

3. Check Unstacked Column Format. Select After, Before and click Numeric Data Variables (Y). H0: Mean Diff = 0, Ha: "Less Than", check "Assume Equal Variances":



4. Click OK. Results:

2 Sample t-test		
H0: Mean Difference = 0		
Ha: Mean Difference Less Than 0		
Assume Equal Variance		
	After	Before
Count	10	10
Mean	6.5800	7.6000
Standard Deviation	1.8707	0.951023
Mean Difference	-1.02	
Std Error Difference	0.663626	
DF	18	
t	-1.5370	
p-value (1-sided)	0.0708	
UC (1-sided, 95%)	0.130770	

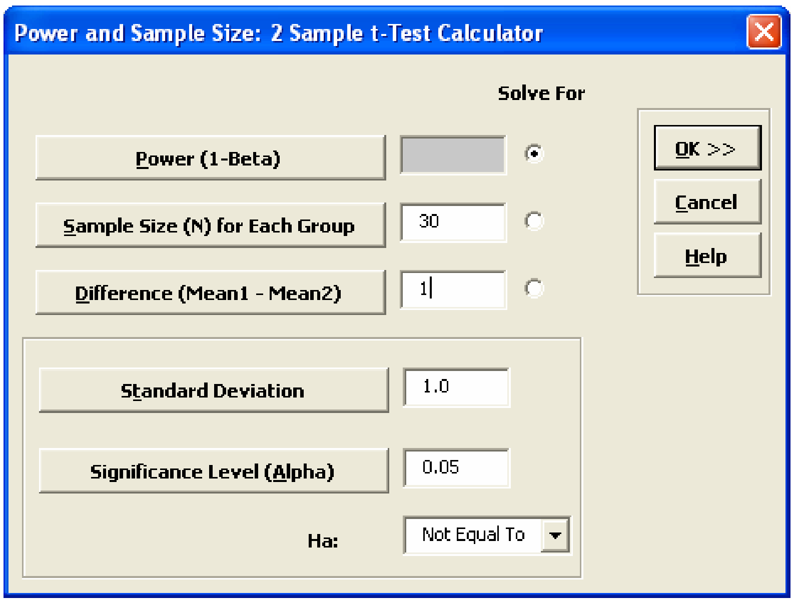
Now the p-value is .07, indicating a fail to reject H0. What changed? Hint: Compare the SE Mean of the Paired t-test to the Std Error Difference of the unpaired two-sample t-test. Where does the additional variability come from in the two-sample t-test? The paired t-test is the appropriate test to use here.

Power & Sample Size for 2 Sample T-Test

To determine Power & Sample Size for a 2 Sample t-Test, you can use the Power & Sample Size Calculator or Power & Sample Size with Worksheet.

1. Click SigmaXL > Statistical Tools > Power & Sample Size Calculators > 2 Sample t-Test Calculator

2. Select "Solve For" Power (1 – Beta). Enter Sample Size and Difference as shown:



Note that we are calculating the power or likelihood of detection given that Mean1 – Mean2 = 1, with sample size for each group = 30, standard deviation = 1, significance level = .05, and Ha: Not Equal To (two-sided test).

3. Click OK. The resulting report is displayed:

Power and Sample Size: 2 Sample t Test

H0: Mean 1 = Mean 2
Ha: Mean 1 ≠ Mean 2
Solve For: Power (1 - Beta)

Sample Size (N)	Difference	Standard Deviation	Significance Level (Alpha)	Power (1 - Beta)
30	1	1	0.05	0.967708259

A power value of 0.97 is good, hence we have the basis for the "minimum sample size n=30" rule of thumb used for continuous data.

4. To determine Power & Sample Size using a Worksheet, click SigmaXL > Statistical Tools > Power & Sample Size with Worksheet > 2 Sample t-Test.

5. A graph showing the relationship between Power, Sample Size and Difference can then be created using SigmaXL > Statistical Tools > Power & Sample Size Chart. See Part E for an example using the 1 Sample t-Test.

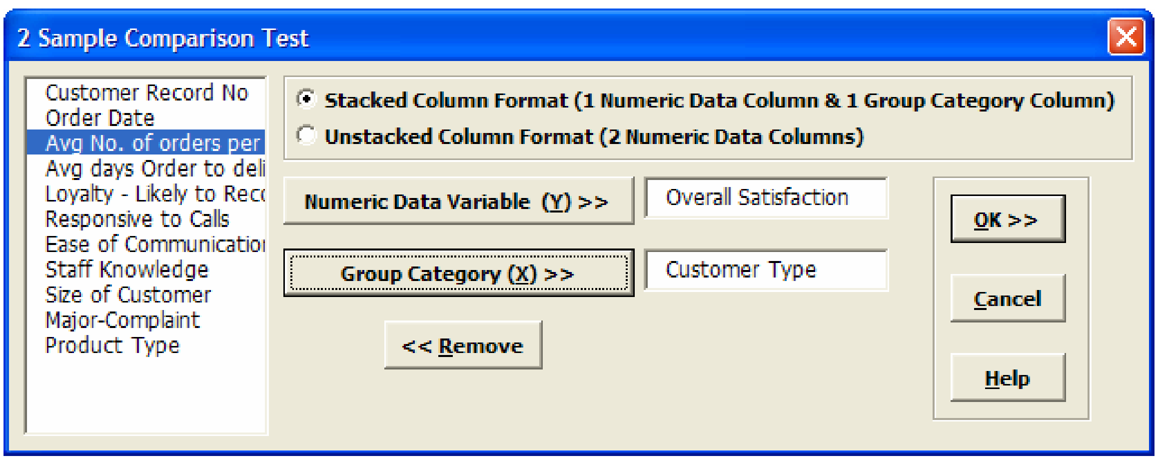
Part H – Two Sample Comparison Test

We will now do a full comparison test of Customer Satisfaction for Customer Type 1 and 2. This test checks each sample for normality, equal variance (F-test and Levene's), 2 sample t-test (assuming equal and unequal variance), and Mann Whitney test for equal Medians. Depending on the normality, variance, and sample size results, the appropriate p-values are highlighted in yellow.

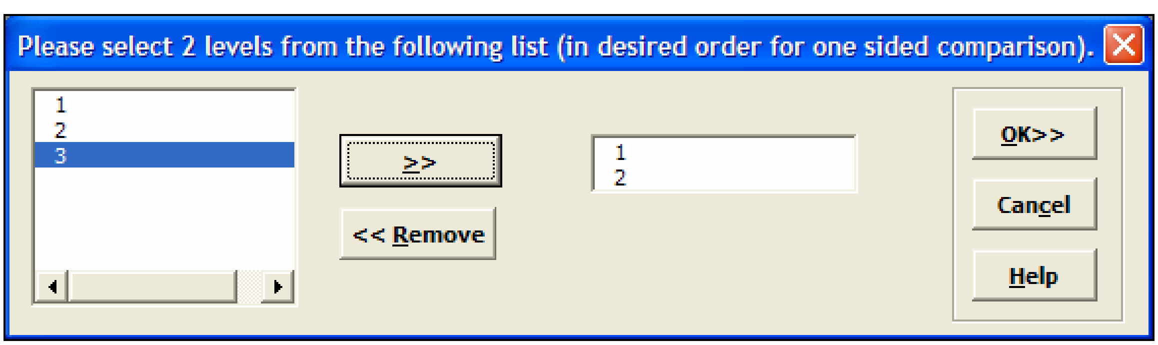
Two Sample Comparison Test

1. Open **Customer Data.xls**, click on Sheet 1 Tab.

2. Click SigmaXL > Statistical Tools > 2 Sample Comparison Tests. Click Next. Check Stacked Column Format. Select Overall Satisfaction as Y, and Customer Type as X.



3. Click OK. Select Customer Type 1 and 2.



4. Click OK.

2 Sample Comparison Test - Overall Satisfaction		
Customer Type	**1**	**2**
Count	31	42
Mean	3.3935	4.2052
Median	3.5600	4.3400
Standard Deviation	0.824680	0.621200
AD Normality Test p-value	0.5306	0.0302
Test for Equal Variances:		
F-test (use with normal data):		
F	1.7624	
p-value (2-sided)	0.0916	
Levene's test (use with non-normal data):		
p-value (2-sided)	0.0443	
2 Sample t-test for means:		
Assume Equal Variance:		
t	-4.7991	
p-value (2-sided)	0.0000	
p-value (1-sided)	0.0000	
Assume Unequal Variance:		
t	-4.6007	
p-value (2-sided)	0.0000	
p-value (1-sided)	0.0000	
2 Sample Mann-Whitney test for medians:		
p-value (2-sided)	0.0000	
p-value (1-sided)	0.0000	

Test 1: Anderson Darling
H0: Data is Normal
Ha: Data is Not Normal

Test 2: Equal Variances
H0: $\sigma_1^2 = \sigma_2^2$
Ha: $\sigma_1^2 \neq \sigma_2^2$

Test 3: Equal Means
H0: $\mu_1 = \mu_2$
Ha: $\mu_1 \neq \mu_2$

Test 4: Equal Medians
H0: $Median_1 = Median_2$
Ha: $Median_1 \neq Median_2$

Customer Type 2 has non-normal data. This makes Levene's test the appropriate test for unequal variance. Levene's test indicates that Customer type 2 has a significantly lower variance, or standard deviation. The lower standard deviation translates to a **consistent** level of satisfaction.

Since Levene's test indicates unequal variance, the appropriate t-test assumes unequal variance. The t-test indicates that Customer Type 2 has a significantly higher mean satisfaction.

Clearly the next step would be to determine a root cause or best practices to reduce the variability in overall satisfaction and increase the mean for all customer types.

Part I – Two Sample Nonparametric Test: Mann-Whitney

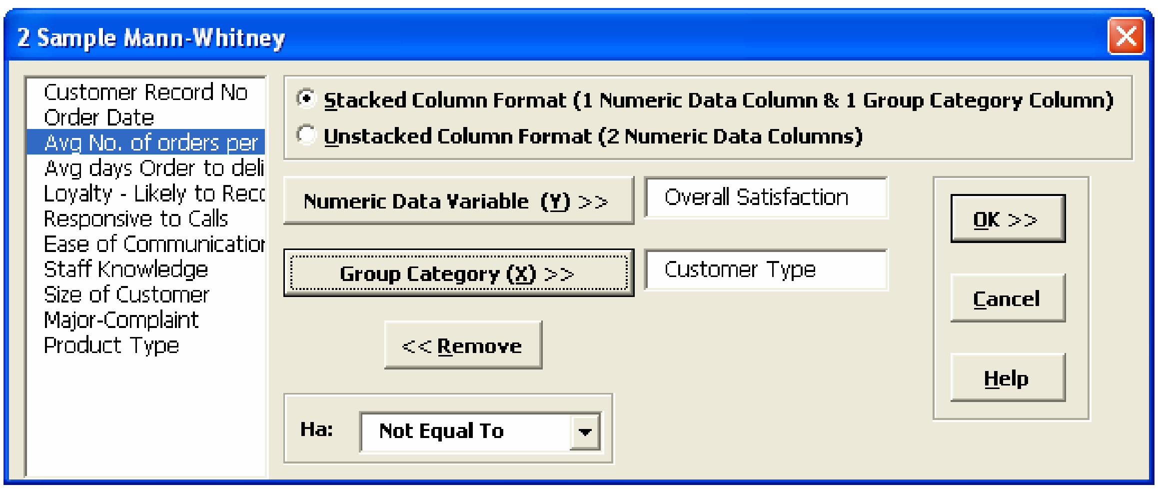
Two Sample Mann-Whitney Rank Test

We will look at comparing medians of Customer Satisfaction by Customer Type, using the Two Sample Mann-Whitney Rank test.(H0: Median2 = Median3, Ha: Median2 ≠ Median3). The Two Sample Mann-Whitney Test is the nonparametric equivalent to the parametric Two Sample t-Test.:

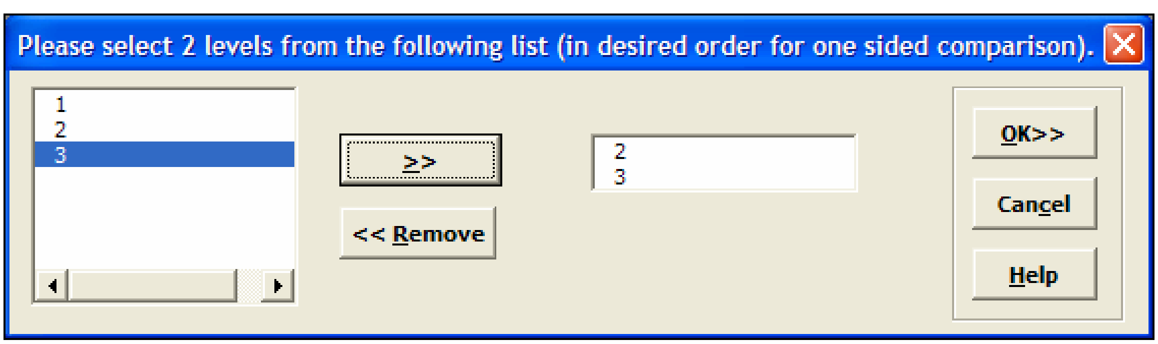
1. Open **Customer Data.xls**, click Sheet 1 tab (or press **F4** to activate last worksheet).

2. Click SigmaXL > Statistical Tools > Nonparametric Tests > 2 Sample Mann-Whitney. If necessary, check Use Entire Data Table, click Next.

3. With stacked column format checked, select Overall Satisfaction as Numeric Data Variable Y; Customer Type as Group Category X; and Ha: "Not Equal To":



4. Click OK. Select Customer Type 2 and 3.



5. Click OK. Resulting output:

2 Sample Mann-Whitney Test - Overall Satisfaction		
H0: Median Difference = 0		
Ha: Median Difference ≠ 0		
Customer Type	2	3
Count	42	27
Median	4.34	3.51
Mann-Whitney Statistic	1744.00	
p-value (2-sided, adjusted for ties)	0.0008	

Given the p-value of .0008 we reject H0 and conclude that Median Customer Satisfaction is significantly different between Customer types 2 and 3. This confirms previous findings and matches the results of the 2 Sample t-Test.

Part J – One-Way ANOVA & Means Matrix

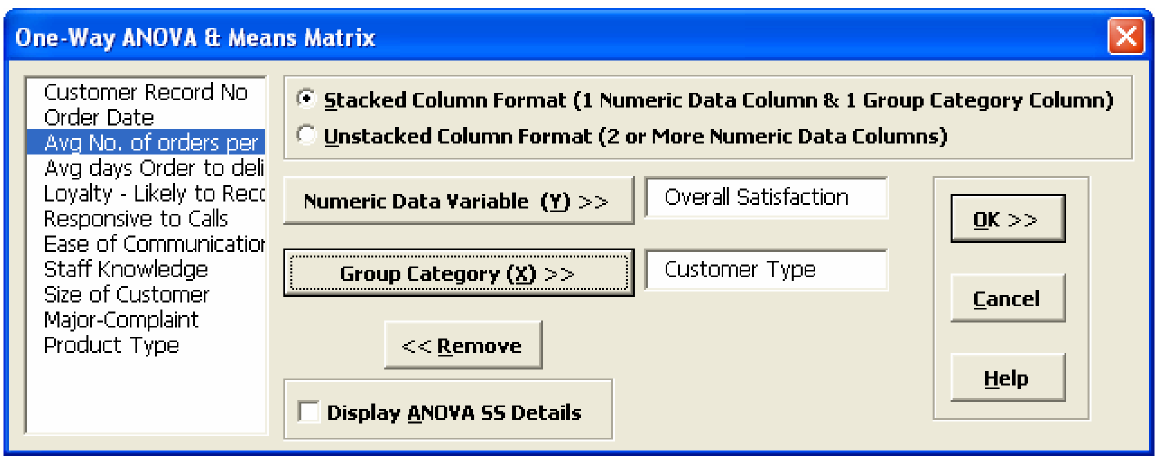
One-Way ANOVA & Means Matrix

1. One-Way ANOVA and Means Matrix allows you to quickly do multiple pairwise comparisons. The One-Way ANOVA tests H0: µ1 = µ2 = µ3; Ha: at least one pairwise set of means are not equal.

2. Open **Customer Data.xls**, click on Sheet 1 tab (or press **F4** to activate last worksheet).

3. Click SigmaXL > Statistical Tools > One-Way ANOVA & Means Matrix. Ensure that the entire data table is selected. If not, check "Use Entire Data Table".

4. Click Next. Ensure that "Stacked Column Format" is checked. Select Overall Satisfaction as Y, and Customer Type as X.

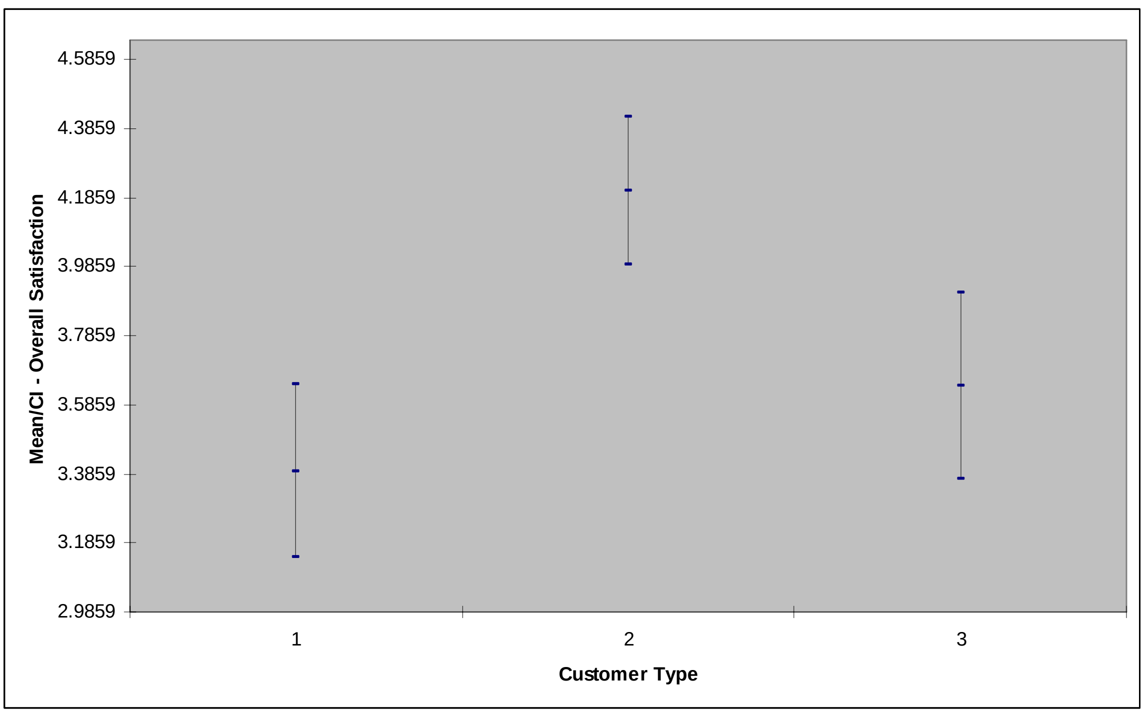


5. Click OK. The results are shown below:

Means Matrix & One-Way ANOVA: Overall Satisfaction				
Customer Type	1	2	3	
Count	31	42	27	
Mean	3.3935	4.2052	3.6411	
Standard Deviation	0.824680	0.621200	0.670478	
UC (2-sided, 95%, pooled)	3.6441	4.4205	3.9096	
LC (2-sided, 95%, pooled)	3.1430	3.9900	3.3727	
ANOVA:				
Pooled Standard Deviation =	0.702810		R-Sq =	20.95%
DF =	97		R-Sq adj. =	19.32%
F =	12.856			
p-value =	0.0000			

Pairwise Mean Difference (row - column)	1	2	3
1	0	-0.811690	-0.247563
2		0	0.564127
3			0

Pairwise Probabilities	1	2	3
1		0.0000	0.1840
2			0.0016
3			



6. The ANOVA p-value of 0.0000 tells us that at least one pairwise set of means are not equal. From the means matrix, we conclude that Mean Overall Satisfaction is significantly different between Customer Type 2 and 3, as well as 1 and 2.

7. A graphical view of the Overall Satisfaction Mean and 95% Confidence Intervals are given to complement the Means Matrix. The fact that the CI's for Customer Type 2 do not overlap those of Type 1 or 3, clearly shows that Customer Type 2 has a significantly higher mean satisfaction score. The overlap of CI's for Type 1 and 3 shows that the mean satisfaction scores for 1 and 3 are not significantly different.

8. The R-Square (R-Sq) value of 20.95% indicates that Customer type "explains" approximately 21% of the variation in Overall Satisfaction. We need to "drill down" to understand the root causes and best practices associated with Customer Type 2.

9. Note that the p-value for 2-3 is slightly different than the previous two sample test result because the variances from all 3 customer types are "pooled" here. This also results in slightly different confidence intervals. One-Way ANOVA & Means Matrix assume equal variance, but analysis above in Part H indicates that this assumption is not true, so this analysis should be treated with caution. An alternative nonparametric test is the Kruskal-Wallis test for Medians (SigmaXL > Statistical Tools > Nonparametric Tests > Kruskal-Wallis Median Test) or Mood's Median (SigmaXL > Statistical Tools > Nonparametric Tests > Mood's Median Test). These are discussed in Part L.

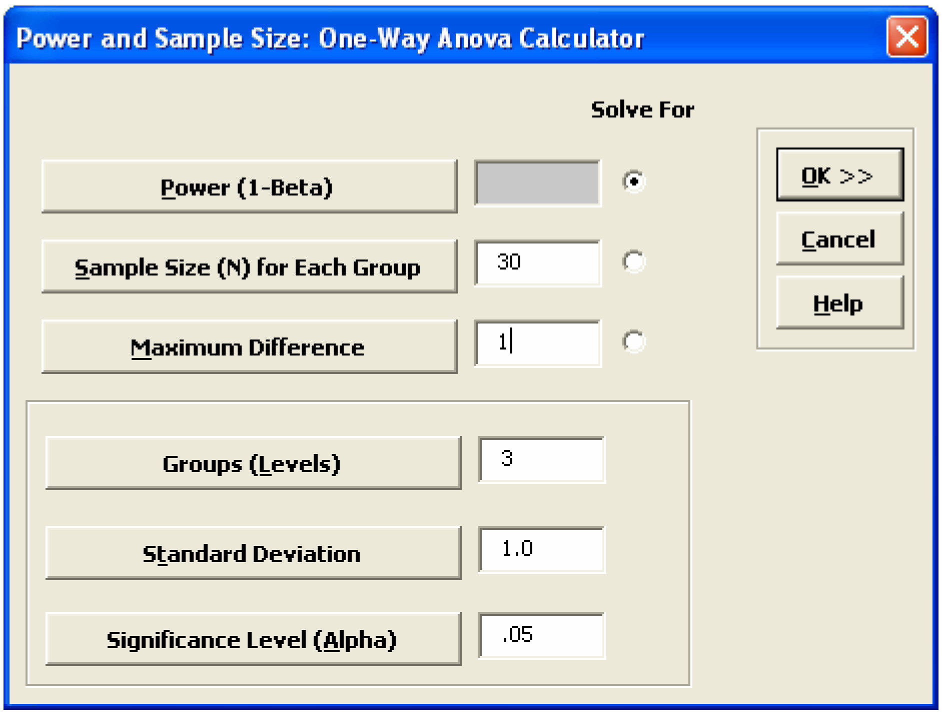
   Note also that the means matrix p-values could easily trigger type I errors when the number of X levels gets large. You should only consider the results of the Means Matrix if the ANOVA p-value is < .05.

Power & Sample Size for One-Way ANOVA

To determine Power & Sample Size for a One-Way ANOVA, you can use the Power & Sample Size Calculator or Power & Sample Size with Worksheet.

1. Click SigmaXL > Statistical Tools > Power & Sample Size Calculators > One-Way ANOVA Calculator.

2. Select "Solve For" Power (1 – Beta). Enter Sample Size and Maximum Difference as shown:



Note that we are calculating the power or likelihood of detection given that the maximum difference between group means = 1, with sample size for each group = 30, 3 groups, standard deviation = 1, significance level = .05, and Ha: Not Equal To (two sided test).

3. Click OK. The resulting report is displayed:

Power and Sample Size: One-Way ANOVA

H0: Mean 1 = Mean 2 = ... = Mean k
Ha: At least one pair Mean i ≠ Mean j
Solve For: Power (1 - Beta)

Sample Size (N)	Maximum Difference	Groups	Standard Deviation	Significance Level (Alpha)	Power (1 - Beta)
30	1	3	1	0.05	0.936276828

A power value of 0.94 is acceptable. Note that this value is less than the power value of 0.97 obtained with the two-sample t-Test.

4. Press **F3** or click "Recall SigmaXL Dialog" to recall last dialog. Change the number of groups to 4. Note that the power value is 0.907. If the number of groups (levels) increase, you will have to increase the sample size in order to maintain statistical power.

5. To determine Power & Sample Size using a Worksheet, click SigmaXL > Statistical Tools > Power & Sample Size with Worksheet > One-Way ANOVA.

6. A graph showing the relationship between Power, Sample Size and Maximum Difference can then be created using SigmaXL > Statistical Tools > Power & Sample Size Chart. See Part E for an example using the 1 Sample t-Test.

Part K – Tests for Equal Variance & Welch's ANOVA

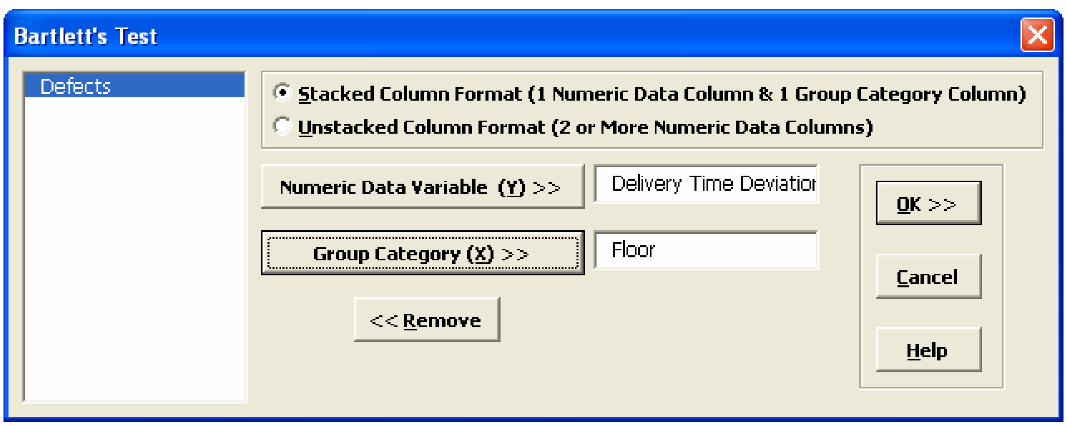
Bartlett's Test

Bartlett's Test is similar to the 2 sample F-Test (SigmaXL > Statistical Tools > 2 Sample Comparison Test) but allows for multiple group comparison of variances (or standard deviations). Like the F-Test, Bartlett's requires that the data from each group be normally distributed but is more powerful than Levene's Test.

1. Open **Delivery Times.xls**, click on Sheet 1 tab.

2. Click SigmaXL > Statistical Tools > Equal Variance Tests > Bartlett. Ensure that the entire data table is selected. If not, check "Use Entire Data Table".

3. Click Next. Ensure that "Stacked Column Format" is checked. Select Delivery Time Deviation as Y, and Floor as X.



4. Click OK. The results are shown below:

Bartlett's Test For Equal Variance: Delivery Time Deviation										
(Use with normal data)										
H0: Variance 1 = Variance 2 = ... = Variance k										
Ha: At least one pair Variance i ≠ Variance j										
Floor	1	2	3	4	5	6	7	8	9	10
Count	73	73	73	73	73	72	72	72	72	72
Mean	4.9886	6.064229	6.24156	5.580593	6.2498	8.004451	6.647356	3.648524	6.539392	6.08361
Median	4.8466	6.4114	6.4764	6.0607	7.1483	7.26055	5.9063	3.6188	6.7994	6.3931
StDev	7.019197	7.611674	7.78235	6.827311	7.608293	6.222518	7.0153	6.682154	7.634089	6.652561
AD Normality Test P-value	0.8084	0.9515	0.4024	0.7642	0.0693	0.4844	0.1543	0.4230	0.4014	0.1475
Bartlett's Test Statistic	7.072946									
P-value	0.6295									

5. With the p-value = 0.63 we fail to reject H0; we do not have evidence to show that the group variances are unequal (practically speaking we will assume that the variances are equal).

6. All 10 Anderson-Darling Test P-values are > .05 indicating that all group data are normal. Since the assumption of normality is met, Bartlett's is the appropriate test to use. If any one of the groups have a low p-value for the Normality test, then Levene's test should be used.

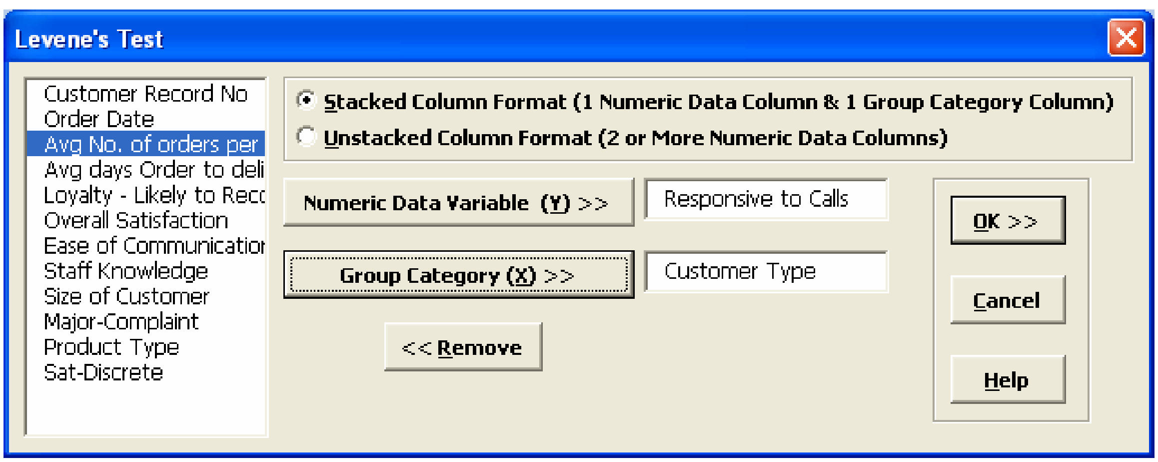
Levene's Test

Levene's Test for multiple group comparison of variances is less powerful that Bartlett's Test, but is robust to the assumption of normality. (This is a modification of the original Levene's Test, sometimes referred to as the Browne-Forsythe Test).

1. Open **Customer Data.xls**, click on Sheet 1 tab.

2. Click SigmaXL > Statistical Tools > Equal Variance Tests > Levene. Ensure that the entire data table is selected. If not, check "Use Entire Data Table".

3. Click Next. Ensure that "Stacked Column Format" is checked. Select Responsive to Calls as Y, and Customer Type as X.



4. Click OK. The results are shown below:

Levene's Test For Equal Variance: Responsive to Calls			
(Use with non-normal data)			
H0: Variance 1 = Variance 2 = ... = Variance k			
Ha: At least one pair Variance i ≠ Variance j			
Customer Type	1	2	3
Count	31	42	27
Mean	3.411613	4.22619	3.821481
Median	3.5	4.72	4.18
StDev	1.3045	0.921232	1.091543
AD Normality Test P-value	0.0021	0.0000	0.0190
Levene's Test Statistic	4.433209		
DF Num	2		
DF Den	97		
P-value	0.0144		

5. The Levene's Test p-value of 0.0144 tells us that we reject H0. At least one pairwise set of variances are not equal. The normality test p-values indicate that all 3 groups have non-normal data (p-values < .05). Since Levene's Test is robust to the assumption of normality, it is the correct test for equal variances (rather than Bartlett's Test).

6. Now that we have determined that the variances (and standard deviations) are not equal, we are presented with a problem if we want to apply classical One-Way ANOVA to test for equal group means. ANOVA assumes that the group variances are equal. A modified ANOVA called Welch's ANOVA can be used as an alternative here.

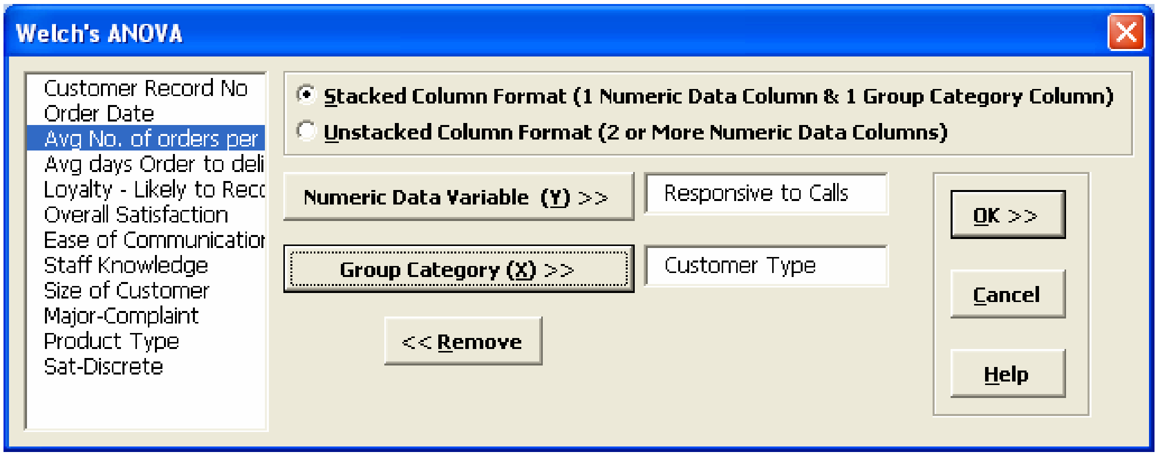
Welch's ANOVA Test

Welch's ANOVA is a test for multiple comparison of means. It is a modified One-Way ANOVA that is robust to the assumption of equal variances. Welch's ANOVA is an extension of the 2 sample t-test for means, assuming unequal variance (SigmaXL > Statistical Tools > 2 Sample Comparison Tests). Nonparametric methods could also be used here but they are not as powerful as Welch's ANOVA.

1. Open **Customer Data.xls**, click on Sheet 1 tab (or press **F4** to activate last worksheet).

2. Click SigmaXL > Statistical Tools > Equal Variance Tests > Welch's ANOVA. Ensure that the entire data table is selected. If not, check "Use Entire Data Table".

3. Click Next. Ensure that "Stacked Column Format" is checked. Select Responsive to Calls as Y, and Customer Type as X.



4. Click OK. The results are shown below:

Welch's ANOVA: Responsive to Calls			
(Use if groups have unequal variance)			
H0: Mean 1 = Mean 2 = ... = Mean k			
Ha: At least one pair Mean i ≠ Mean j			
Customer Type	**1**	**2**	**3**
Count	31	42	27
Mean	3.411613	4.22619	3.821481
Median	3.5	4.72	4.18
StDev	1.3045	0.921232	1.091543
AD Normality Test P-value	0.0021	0.0000	0.0190
Welch's F Ratio	4.654319		
DF Num	2		
DF Den	55.75311		
P-value	0.0135		

5. The p-value for Welch's ANOVA is 0.0135, therefore we reject H0 and conclude that the group means for Responsive to Calls are not equal. We will explore the relationship between Overall Satisfaction and Responsive to Calls later.

Part L – Nonparametric Multiple Comparison

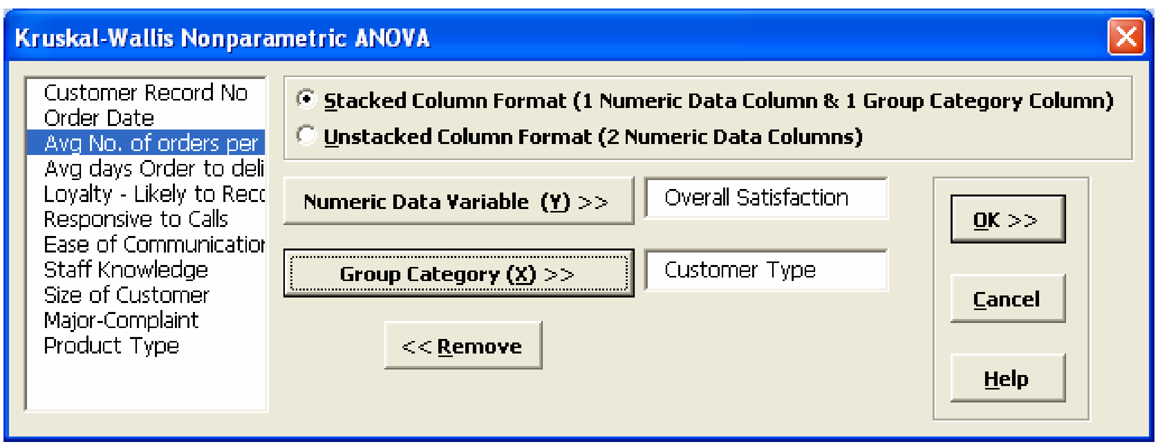
Kruskal-Wallis Test

The Kruskal-Wallis test is an extension of the Mann-Whitney Rank test, allowing for more than 2 samples. It is a nonparametric equivalent to the parametric One-Way ANOVA. The Null Hypothesis is: H0: Median1 = Median2 = … = MedianK. Ha: At least two Medians are different.

1. Open **Customer Data.xls**, click on Sheet 1 tab (or press **F4** to activate last worksheet).

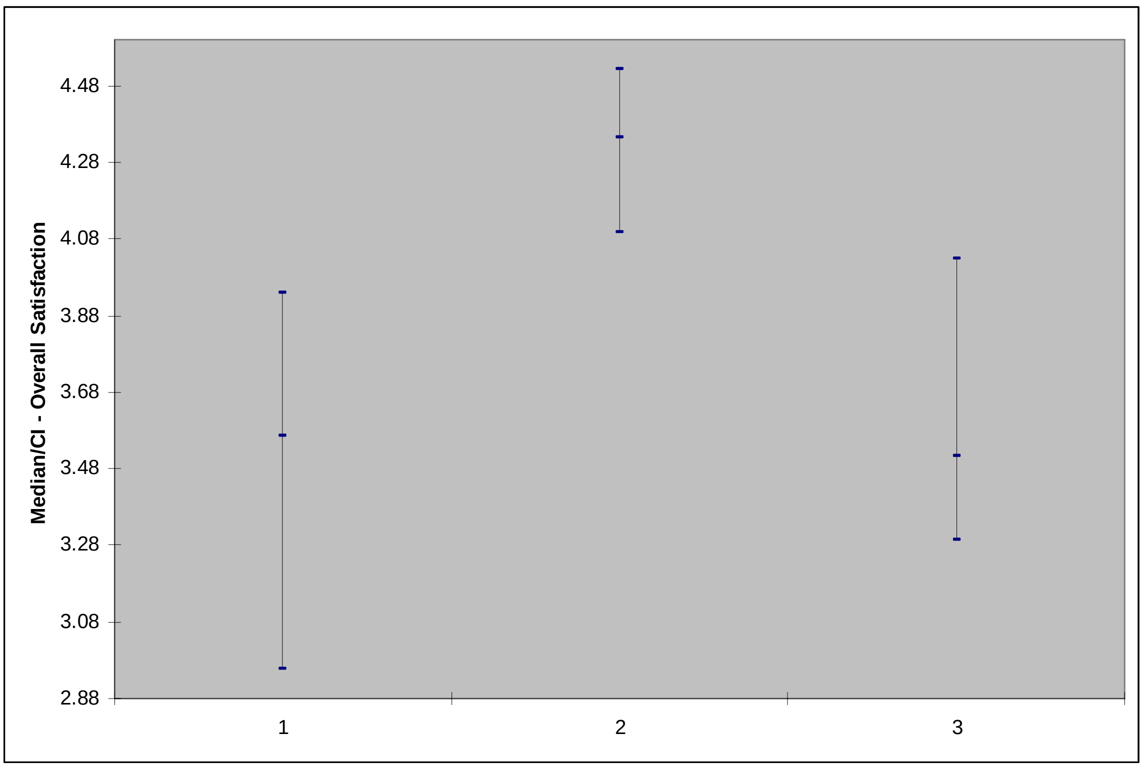
2. Click SigmaXL > Statistical Tools > Nonparametric Tests > Kruskal-Wallis Median Test. Ensure that the entire data table is selected. If not, check "Use Entire Data Table".

3. Click Next. Ensure that "Stacked Column Format" is checked. Select Overall Satisfaction as Y, and Customer Type as X.



4. Click OK. The results are shown below:

Kruskal-Wallis Nonparametric ANOVA: Overall Satisfaction			
H0: Median 1 = Median 2 = ... = Median k			
Ha: At least one pair Median i ≠ Median j			
	1	2	3
Count (N)	31	42	27
Median	3.56	4.34	3.51
UC Median (2-sided, 95%)	3.9362	4.5184	4.0227
LC Median (2-sided, 95%)	2.9535	4.0946	3.2891
Z	-3.3389	4.5290	-1.5567
Kruskal-Wallis Statistic (H)	21.360		
DF	2		
p-value (2-sided, adjusted for ties)	0.0000		



The p-value of 0.0000 tells us that we reject H0. At least one pairwise set of medians are not equal.

5. The Kruskal-Wallis Statistic is based on comparing mean ranks for each group versus the mean rank for all observations. The Z value for Customer Type 3 is –1.56, the smallest absolute Z-value. This size indicates that the mean rank for Type 3 differed least from the mean rank for all observations. The Z value for Customer Type 2 is 4.53, the largest absolute Z-value. This size indicates that the mean rank differed most from the mean rank for all observations.

6. A graphical view of the Overall Satisfaction Median and 95% Confidence Intervals are given to complement the Z scores. The fact that the CI's for Customer Type 2 do not overlap those of Type 1 or 3, clearly shows that Customer Type 2 has a significantly higher median satisfaction score. The overlap of CI's for Type 1 and 3 shows that the median satisfaction scores for 1 and 3 are not significantly different.

Mood's Median Test

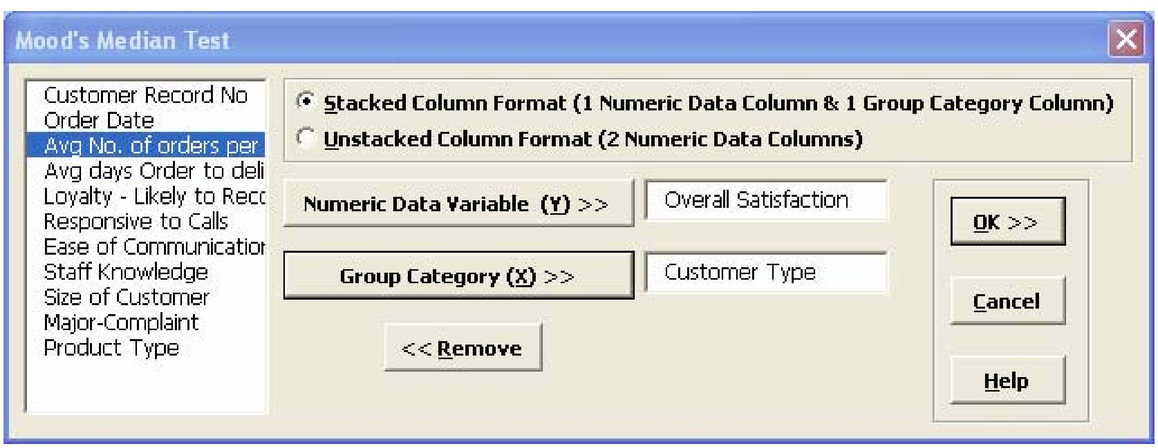
Mood's Median Test is an extension of the One Sample Sign Test, using Chi-Square as the test statistic. Like the Kruskal-Wallis test, Mood's median test can be used to test the equality of medians from multiple samples. It provides a nonparametric alternative to the one-way analysis of variance. The Null Hypothesis is: H0: Median1 = Median2 = … = MedianK. Ha: At least two Medians are different.

Mood's median test is more robust to outliers than the Kruskal-Wallis test, but is less powerful in the absence of outliers. You should first look at your data with Boxplots. If there are extreme outliers, then Mood's Median should be used rather than Kruskal-Wallis.

1. Open **Customer Data.xls**, click on Sheet 1 tab (or press **F4** to activate last worksheet).

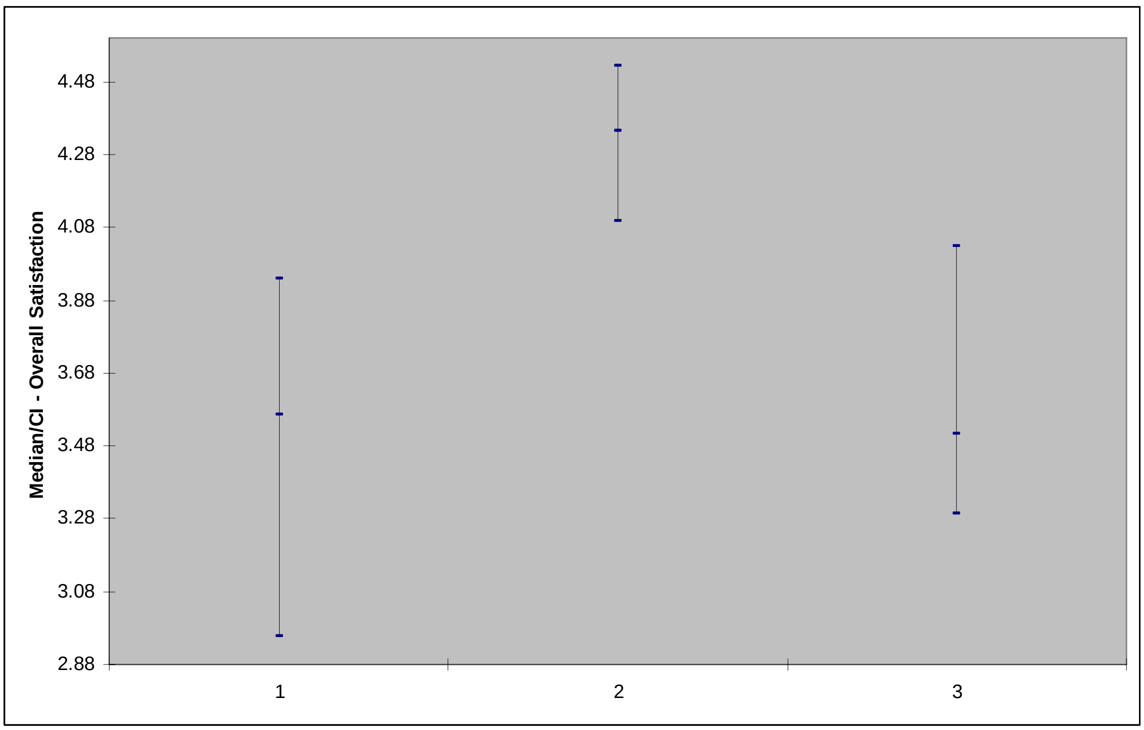
2. Click SigmaXL > Statistical Tools > Nonparametric Tests > Mood's Median Test. Ensure that the entire data table is selected. If not, check "Use Entire Data Table".

3. Click Next. Ensure that "Stacked Column Format" is checked. Select Overall Satisfaction as Y, and Customer Type as X.



4. Click OK. The results are shown below:

Mood's Median Test: Overall Satisfaction			
H0: Median 1 = Median 2 = ... = Median k			
Ha: At least one pair Median i ≠ Median j			
	1	2	3
Count (N <= Overall Median)	21	12	17
Count (N > Overall Median)	10	30	10
Median	3.5600	4.3400	3.5100
UC Median (2-sided, 95%)	3.9362	4.5184	4.0227
LC Median (2-sided, 95%)	2.9535	4.0946	3.2891
Overall Median	3.9450		
Chi-Square	13.432		
DF	2		
p-value (2-sided)	0.0012		



The p-value of 0.0012 tells us that we reject H0. At least one pairwise set of medians are not equal.

5. A graphical view of the Overall Satisfaction Median and 95% Confidence Intervals are given. This is the same graph provided in the Kruskal-Wallis test report.

Part M – Nonparametric Runs Test

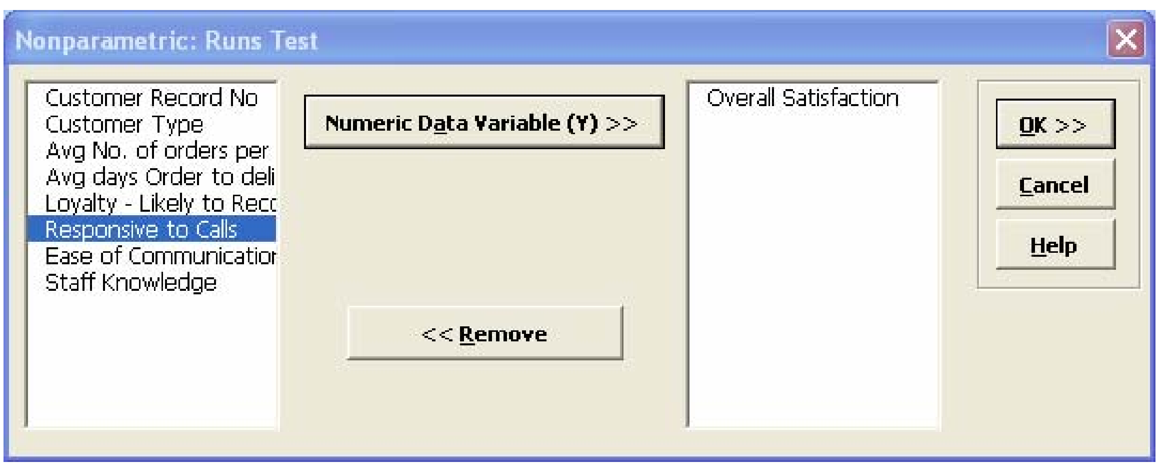
Nonparametric Runs Test for Randomness

The nonparametric runs test provides a test for randomness or independence. The null hypothesis is H0: The data is random (or independent). The alternative hypothesis is Ha: The data is not random (or independent). Note that this test is also provided as an option in Run Charts (SigmaXL > Graphical Tools > Run Chart). In addition to providing an overall test for randomness, 4 tests are performed to detect Clustering, Mixtures, Trends, and Oscillations. If any of these patterns are significant (typically using $\alpha = 0.01$), we would need to take corrective action before proceeding with further statistical analysis. (Note that SigmaXL will highlight any p-values < .05 in red).

1. Open **Customer Data.xls**, click on Sheet 1 tab (or press **F4** to activate last worksheet).

2. Click SigmaXL > Statistical Tools > Nonparametric Tests > Runs Test. Ensure that the entire data table is selected. If not, check "Use Entire Data Table".

3. Click Next. Select Overall Satisfaction as Y:



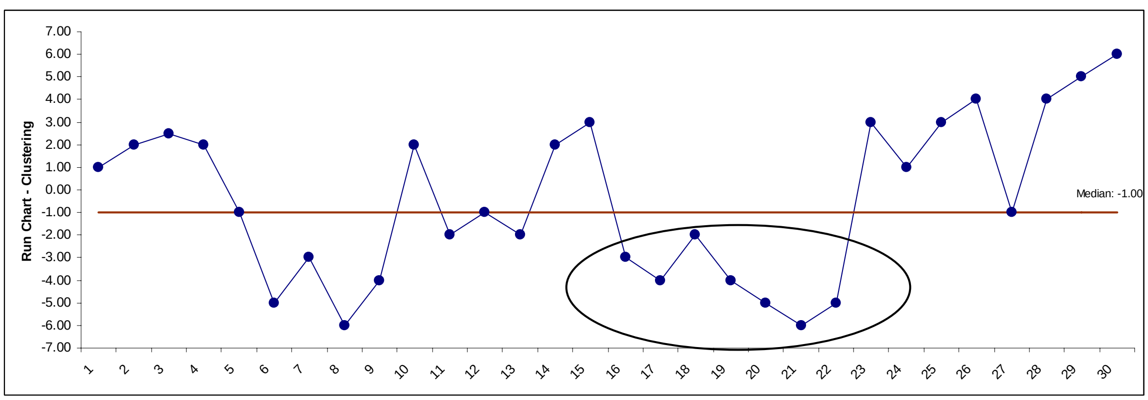
4. Click OK. The resulting report is shown:

Nonparametric Runs Test	
Number of Runs about Median:	44
Expected Number of Runs about Median:	51
Number of Points above Median:	50
Number of Points equal to or below Median:	50
P-Value for Clustering:	0.0797
P-Value for Mixtures:	0.9203
P-Value for Lack of Randomness (2-Sided):	0.1594
	64
Expected Number of Runs Up or Down:	66.33333
P-Value for Trends:	0.2883
P-Value for Oscillation:	0.7117

5. With all of the p-values being greater than 0.01, we fail to reject H0, and conclude that the data is random (or statistically independent). Recall from the run chart of this data that there were no obvious trends or patterns.

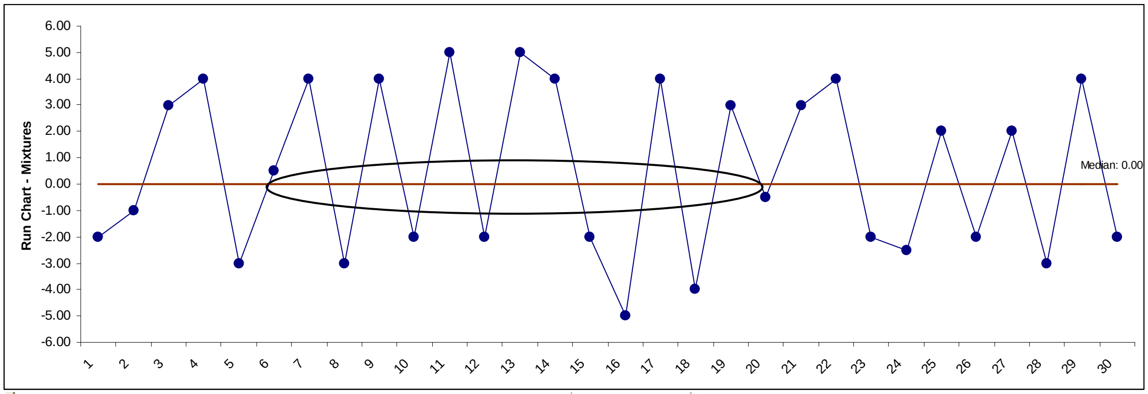
6. Examples of Clustering, Mixtures, Trends, and Oscillations are given below using the Run Chart to illustrate. The data for these examples are given in the file **Runs Test Example Data.xls**.

   a. **Clustering** appears as a group of points in one area of the chart. It may indicate special cause variation such as sampling or measurement problems.



Nonparametric Runs Test: Clustering	
Number of Runs about Median:	9
Expected Number of Runs about Median:	15.93333
Number of Points above Median:	14
Number of Points equal to or below Median:	16
P-Value for Clustering:	0.0048
P-Value for Mixtures:	0.9952
P-Value for Lack of Randomness (2-Sided):	0.0096
Number of Runs Up or Down:	17
Expected Number of Runs Up or Down:	19.66667
P-Value for Trends:	0.1168
P-Value for Oscillation:	0.8832

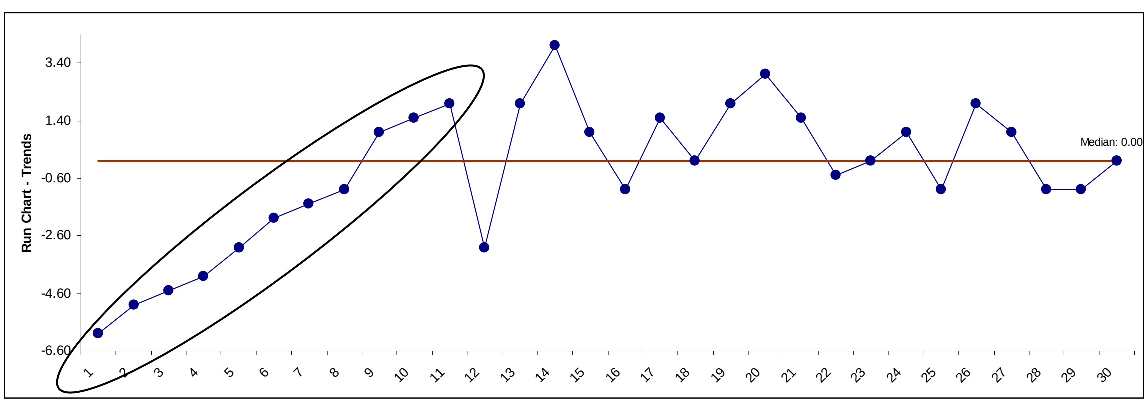
b. **Mixtures** appear as an absence of data points near the center line. A mixture may indicate a bimodal distribution due to a regular change of shift, machinery, or raw materials.



Nonparametric Runs Test: Mixtures	
Number of Runs about Median:	23
Expected Number of Runs about Median:	16
Number of Points above Median:	15
Number of Points equal to or below Median:	15
P-Value for Clustering:	0.9954
P-Value for Mixtures:	0.0046
P-Value for Lack of Randomness (2-Sided):	0.0093
Number of Runs Up or Down:	22
Expected Number of Runs Up or Down:	19.66667
P-Value for Trends:	0.8514
P-Value for Oscillation:	0.1486

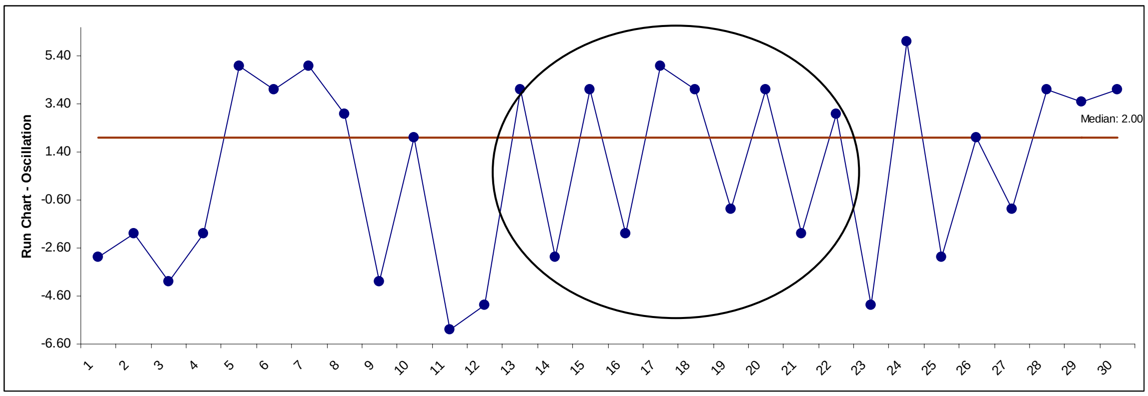
Note that the p-value for Mixtures = 1 – p-value for Clustering. They are mutually exclusive. The p-value for Lack of Randomness = 2 * minimum of (p-value Clustering, p-value Mixtures).

c. **Trends** appear as an upward or downward drift in the data and may be due to special causes such as tool wear.



Nonparametric Runs Test: Trends	
Number of Runs about Median:	13
Expected Number of Runs about Median:	15.73333
Number of Points above Median:	13
Number of Points equal to or below Median:	17
P-Value for Clustering:	0.1504
P-Value for Mixtures:	0.8496
P-Value for Lack of Randomness (2-Sided):	0.3008
Number of Runs Up or Down:	13
Expected Number of Runs Up or Down:	19.66667
P-Value for Trends:	0.0015
P-Value for Oscillation:	0.9985

d. **Oscillations** appear as rapid up/down fluctuations indicating process instability.



Nonparametric Runs Test: Oscillation	
Number of Runs about Median:	16
Expected Number of Runs about Median:	15.93333
Number of Points above Median:	14
Number of Points equal to or below Median:	16
P-Value for Clustering:	0.5099
P-Value for Mixtures:	0.4901
P-Value for Lack of Randomness (2-Sided):	0.9801
Number of Runs Up or Down:	25
Expected Number of Runs Up or Down:	19.66667
P-Value for Trends:	0.9914
P-Value for Oscillation:	0.0086

Note that the p-value for Trends = 1 – p-value for Oscillation. They are mutually exclusive.

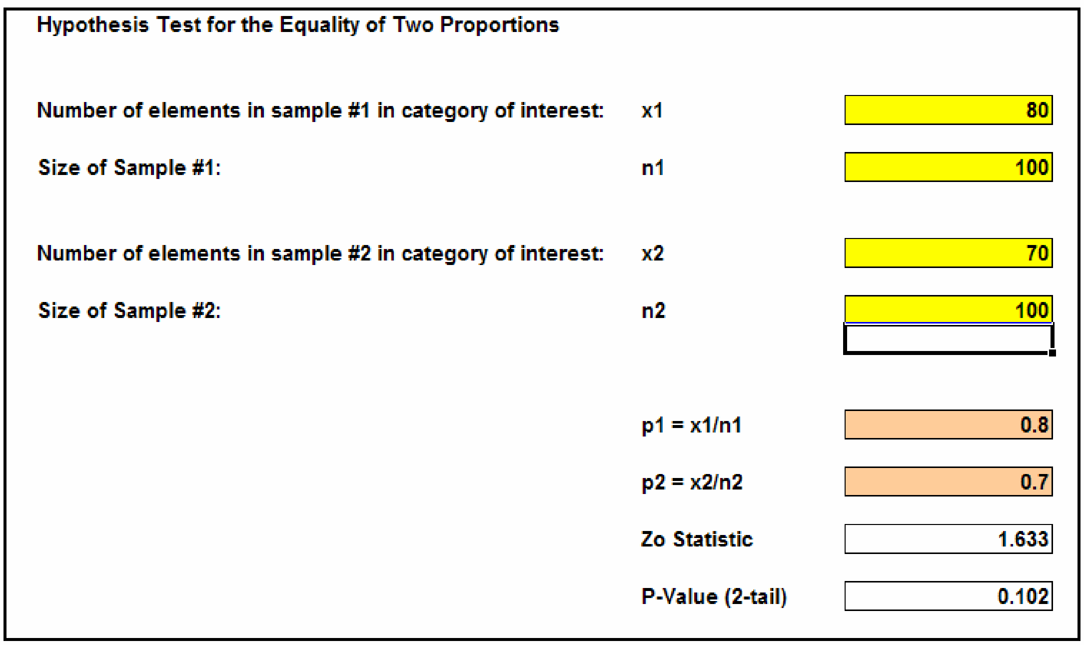
Part N – Attribute/Discrete Data Tests

Attribute/Discrete Data Tests

1. We begin with a scenario where Day Shift is running at 80% Yield and Night Shift has 70% Yield. This data is based on a random sample of 100 units for each Shift, each unit is either good or bad. Question: Is Day shift running differently than Night Shift? Statistically, we call the Null Hypothesis, H0: Proportion P1 = Proportion P2; the alternative hypothesis, Ha is: P1≠P2. If the calculated p-value < .05, then we reject the null hypothesis and conclude that Day Shift and Night Shift are different.

2. Click SigmaXL > Templates & Calculators > 2 Proportions Test.

3. Enter x1 = 80, n1 = 100, x2 = 70, n2 = 100 as shown:



Hypothesis Test for the Equality of Two Proportions

Number of elements in sample #1 in category of interest:	x1	80
Size of Sample #1:	n1	100
Number of elements in sample #2 in category of interest:	x2	70
Size of Sample #2:	n2	100
	p1 = x1/n1	0.8
	p2 = x2/n2	0.7
	Zo Statistic	1.633
	P-Value (2-tail)	0.102

Since the p-value of 0.102 is greater than .05, we fail to reject H0. We do not have enough evidence to show that there is a significant difference between Day Shift and Night shift. This does not mean that we have proven that they are the same. In practice however, we either assume that they are the same or we collect more data.

4. Now enter x1 = 160, n1 = 200, x2 = 140, n2 = 200. Note that the p-value is now .021, so we reject H0.

5. Open the file **Attribute Data.xls**, ensure that Example 1 Sheet is active. This data is in Two –Way Table format, or pivot table format. Note that cells B2:D4 have been pre-selected.

6. Click SigmaXL > Statistical Tools > Chi-Square Test – Two-Way Table Data. Note the selection of data includes the Row and Column labels (if we had Row and Column Totals these would NOT be selected).

7. Click Next. Results:

Chi-Square Table Statistics		
Observed Counts	Day Shift	Night Shift
Pass	80	70
Fail	20	30
Expected Counts	Day Shift	Night Shift
Pass	75	75
Fail	25	25
Std. Residuals	Day Shift	Night Shift
Pass	0.577350	-0.577350
Fail	-1	1
Chi-Square	2.6667	
DF	1	
p-value	0.1025	

The p-value matches that of the 2 proportion test. Since the p-value of 0.1 is greater than .05, we fail to reject H0.

8. Now click Example 2 Sheet tab. The Yields have not changed but we have doubled the sample size. Repeat the above analysis. The resulting output is:

Chi-Square Table Statistics		
Observed Counts	**Day Shift**	**Night Shift**
Pass	160	140
Fail	40	60
Expected Counts	**Day Shift**	**Night Shift**
Pass	150	150
Fail	50	50
Std. Residuals	**Day Shift**	**Night Shift**
Pass	0.816497	-0.816497
Fail	-1.4142	1.4142
Chi-Square	5.3333	
DF	1	
p-value	0.0209	

Since the p-value is < .05, we now reject the Null Hypothesis, and conclude that Day Shift and Night Shift are significantly different. The Residuals tell us that Day Shift failures are less than expected (assuming equal proportions), and Night Shift failures are more than expected.

Note, by doubling the sample size, we improved the power or sensitivity of the test.

9. Click the Example 3 Sheet tab. In this scenario we have 3 suppliers, and an additional marginal level. A random sample of 100 units per supplier is tested. The null hypothesis here is: No relationship between Suppliers and Pass/Fail/Marginal rates, but in this case we can state it as No difference across suppliers. Redoing the above analysis (for selection B2:E5) yields the following:

Chi-Square Table Statistics			
Observed Counts	**Supplier A**	**Supplier B**	**Supplier C**
Pass	80	70	75
Fail	10	15	18
Marginal	10	15	7
Expected Counts	**Supplier A**	**Supplier B**	**Supplier C**
Pass	75	75	75
Fail	14.333	14.333	14.333
Marginal	10.667	10.667	10.667
Std. Residuals	**Supplier A**	**Supplier B**	**Supplier C**
Pass	0.577350	-0.577350	0
Fail	-1.1446	0.176091	0.968497
Marginal	-0.204125	1.3268	-1.1227
Chi-Square	6.0082		
DF	4		
p-value	0.1985		

The p-value tells us that we do not have enough evidence to show that there is a difference across the 3 suppliers.

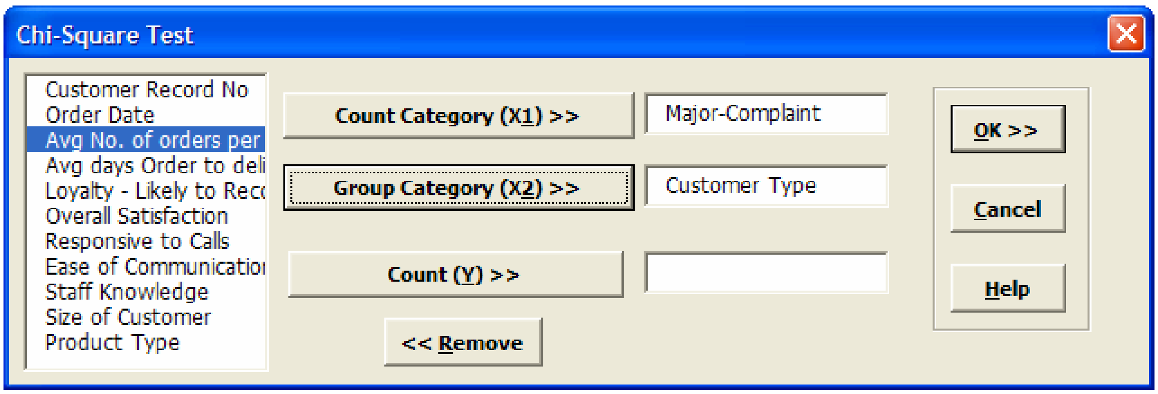
10. Click the Example 4 Sheet tab. Here we have doubled the sample size to 200 per supplier. Note that the percentages are identical to example 3. Redoing the above analysis yields the following:

Chi-Square Table Statistics			
Observed Counts	**Supplier A**	**Supplier B**	**Supplier C**
Pass	160	140	150
Fail	20	30	36
Marginal	20	30	14
Expected Counts	**Supplier A**	**Supplier B**	**Supplier C**
Pass	150	150	150
Fail	28.667	28.667	28.667
Marginal	21.333	21.333	21.333
Std. Residuals	**Supplier A**	**Supplier B**	**Supplier C**
Pass	0.816497	-0.816497	0
Fail	-1.6187	0.249028	1.3697
Marginal	-0.288674	1.8764	-1.5877
Chi-Square	12.016		
DF	4		
p-value	0.0172		

With the p-value < .05 we now conclude that there is a significant difference across suppliers. Examining the residuals tells us that Supplier A has fewer failures than expected (if there was no difference across suppliers) and Supplier C has more failures than expected. Supplier B has more marginal than expected and Supplier C has fewer marginal parts than expected.

11. Open **Customer Data.xls**. Click Sheet 1 tab. The discrete data of interest is Complaints and Customer Type, i.e., does the type of complaint differ across customer type? Formally the Null Hypothesis is that there is no relationship (or independence) between Customer Type and Complaints.

12. Click SigmaXL > Statistical Tools > Chi-Square Test. Select Major-Complaint for X1 and Customer Type for X2.



13. Click OK. Results:

Chi-Square Test			
Major-Complaint - Customer Type			
Observed Counts	1	2	3
Difficult-to-order	5	9	5
Not-available	2	0	2
Order-takes-too-long	1	3	6
Return-calls	19	28	13
Wrong-color	4	2	1
Expected Counts	1	2	3
Difficult-to-order	5.8900	7.9800	5.1300
Not-available	1.2400	1.6800	1.08
Order-takes-too-long	3.1000	4.2000	2.7000
Return-calls	18.600	25.200	16.200
Wrong-color	2.1700	2.9400	1.8900
Std. Residuals	1	2	3
Difficult-to-order	-0.366718	0.361076	-0.057396402
Not-available	0.682500	-1.2961	0.885270
Order-takes-too-long	-1.1927	-0.585540	2.0083
Return-calls	0.092747779	0.557773	-0.795046
Wrong-color	1.2423	-0.548219	-0.647380
Chi-Square	12.211		
DF	8		
p-value	0.1420		
Note: 9 out of 15 cells have expected counts less than 5.			

Here with the p-value = 0.142 we fail to reject H0, so we do not have enough evidence to show a difference in customer complaints across customer types.

Note: If more than 20% of Fitted Cells are Sparse - cells whose expected value is less than 5 – consider collecting more data, consolidation of levels, or removal of columns.

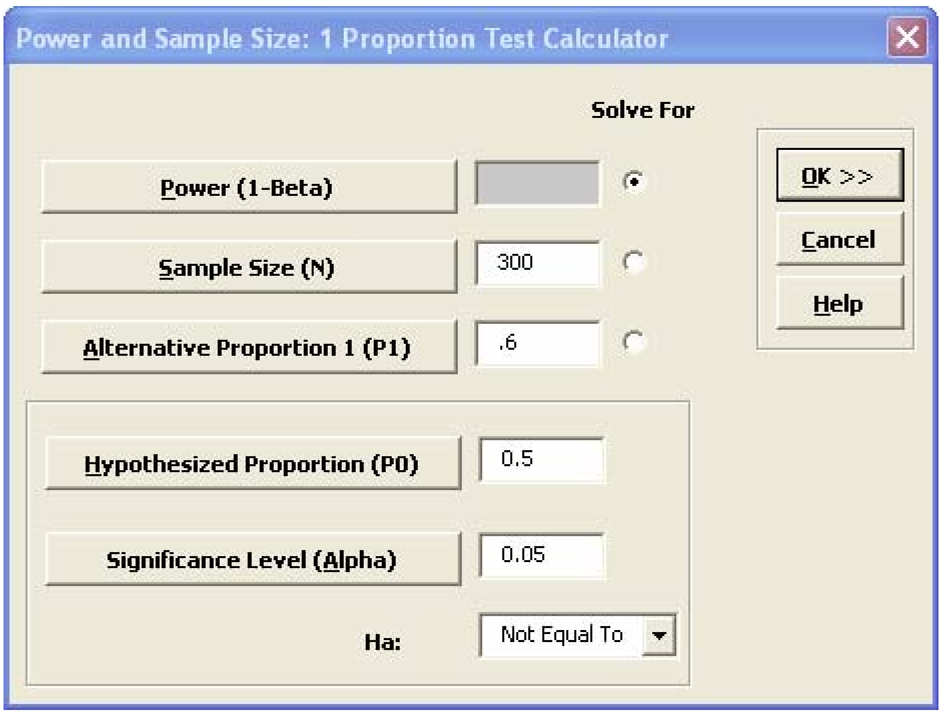
Tip: Use Chi-Square Analysis to complement Advanced Pareto Analysis.

Power & Sample Size for One Proportion Test

To determine Power & Sample Size for a 1 Proportion Test, you can use the Power & Sample Size Calculator or Power & Sample Size with Worksheet.

1. Click SigmaXL > Statistical Tools > Power & Sample Size Calculators > 1 Proportion Test Calculator.

2. Select "Solve For" Power (1 – Beta). Enter Sample Size and Alternative Proportion as shown:



Note that we are calculating the power or likelihood of detection given that the hypothesized proportion is 0.5, but the alternative proportion is 0.6, sample size = 300, significance level = .05, and Ha: Not Equal To (two sided test).

3. Click OK. The resulting report is displayed:

Power and Sample Size: 1 Proportion Test

H0: P0 = 0.5
Ha: P0 ≠ 0.5
Solve For: Power (1 - Beta)

Sample Size (N)	Alternative Proportion (P1)	Hypothesized Proportion (P0)	Significance Level (Alpha)	Power (1 - Beta)
300	0.6	0.5	0.05	0.937627018

A power value of 0.94 is acceptable, but note that the sample size n = 300, and the difference in proportion value is 0.1 or 10%! The sample size requirements for discrete data are much higher than those for continuous data.

4. To determine Power & Sample Size using a Worksheet, click SigmaXL > Statistical Tools > Power & Sample Size with Worksheet > 1 Proportion Test.

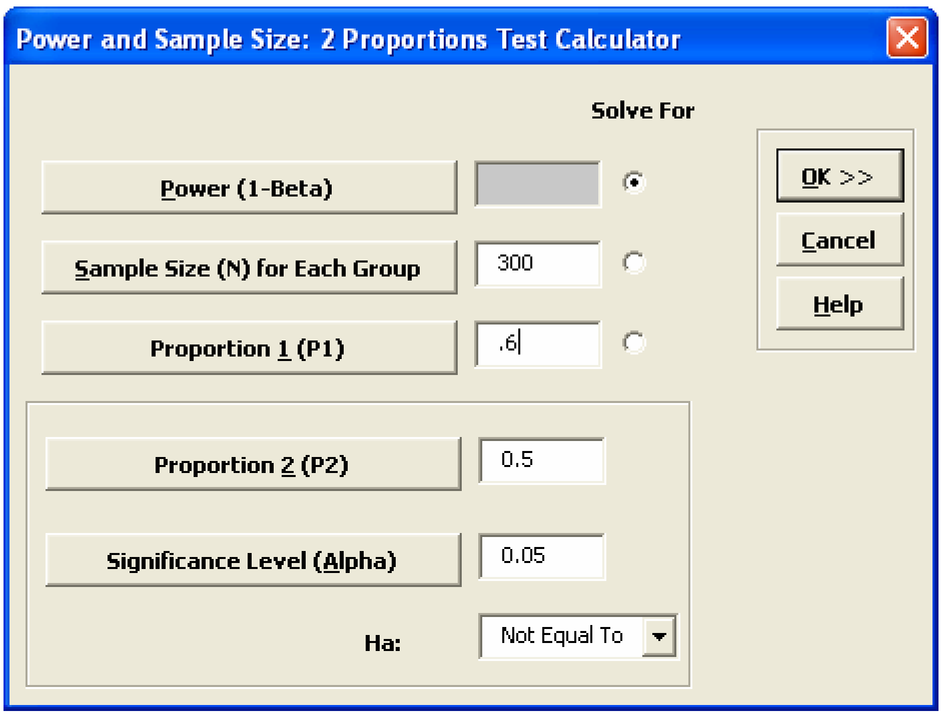
5. A graph showing the relationship between Power, Sample Size and Proportion Value can then be created using SigmaXL > Statistical Tools > Power & Sample Size Chart. See Part E for an example using the 1 Sample t-Test.

Power & Sample Size for Two Proportions Test

To determine Power & Sample Size for a 2 Proportions Test, you can use the Power & Sample Size Calculator or Power & Sample Size with Worksheet.

1. Click SigmaXL > Statistical Tools > Power & Sample Size Calculators > 2 Proportions Test Calculator.

2. Select "Solve For" Power (1 – Beta). Enter Sample Size and Proportion 1 values as shown:



Note that we are calculating the power or likelihood of detection given that P1 = 0.5 and P2 = 0.6, sample size for each group = 300, significance level = .05, and Ha: Not Equal To (two sided test).

3. Click OK. The resulting report is displayed:

Power and Sample Size: 2 Proportions Test				
H0: P1 = P2				
Ha: P1 ≠ P2				
Solve For: Power (1 - Beta)				
Sample Size (N)	Proportion 1 (P1)	Proportion 2 (P2)	Significance Level (Alpha)	Power (1 - Beta)
300	0.6	0.5	0.05	0.693021232

A power value of 0.69 is unacceptable. Note that this value is much less than the power for the one proportion test (0.94).

4. To compensate, we will double the sample size per group. Press **F3** or click "Recall SigmaXL Dialog" to recall last dialog. Change the sample size per group from 300 to 600. Note that the power value is now 0.94.

5. To determine Power & Sample Size using a Worksheet, click SigmaXL > Statistical Tools > Power & Sample Size with Worksheet > 2 Proportions Test.

6. A graph showing the relationship between Power, Sample Size and Proportion Values can then be created using SigmaXL > Statistical Tools > Power & Sample Size Chart. See Part E for an example using the 1 Sample t-Test.

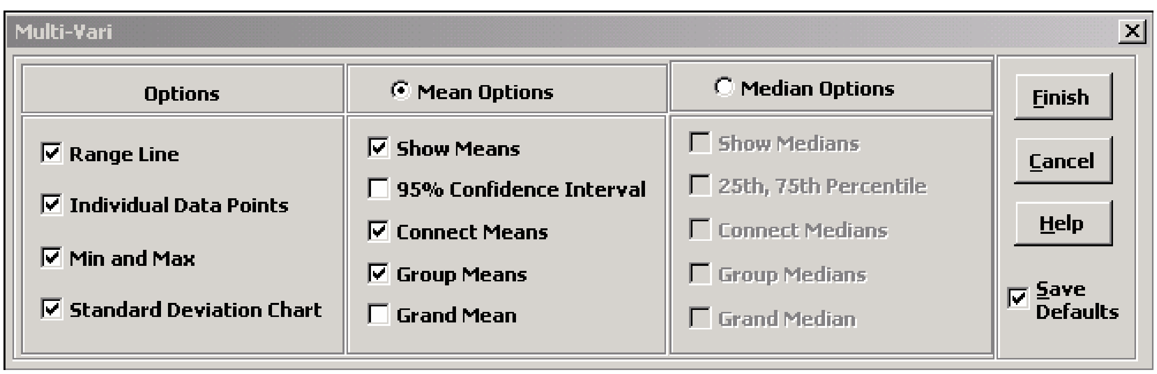
Part O – Multi-Vari Charts

Multi-Vari Charts

The Multi-Vari chart is a powerful tool to identify dominant Sources of Variation (SOV). The three major "families" of variation are: Within Unit, Between Unit, and Temporal (Over Time). We will look at examples of each type of SOV and then use the Multi-Vari Chart to study Overall Satisfaction in the Customer Data.xls file.

1. Open **Within.xls**, click Sheet 1. Select SigmaXL > Graphical Tools > Multi-Vari Options

2. The charts shown will be updated as options are selected. Note that they are for demonstration purposes and are not based on the Customer Data.xls data. Ensure that all general options are selected (Range Line, Individual Data Points, Min and Max, Standard Deviation Chart). Select Mean Options, ensure that Show Means, Connect Means, and Group Means are checked. Ensure that Save Defaults is checked. These settings would be typical for a Multi-Vari chart. (The Median options provide the ability to display percentiles as an alternative to the Means).



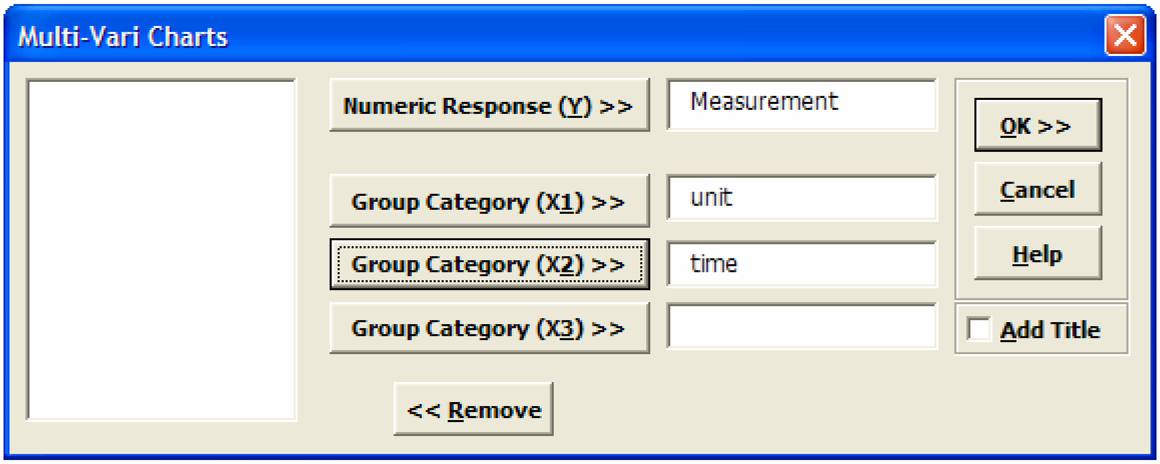
Tip: Multi-Vari Charts can be used to display Confidence Intervals (as we did earlier in Part C). To do this, check the 95% Confidence Interval.

3. Click Finish. SigmaXL automatically starts the Multi-Vari Chart procedure (this is equivalent to clicking SigmaXL > Graphical Tools > Multi-Vari Charts).

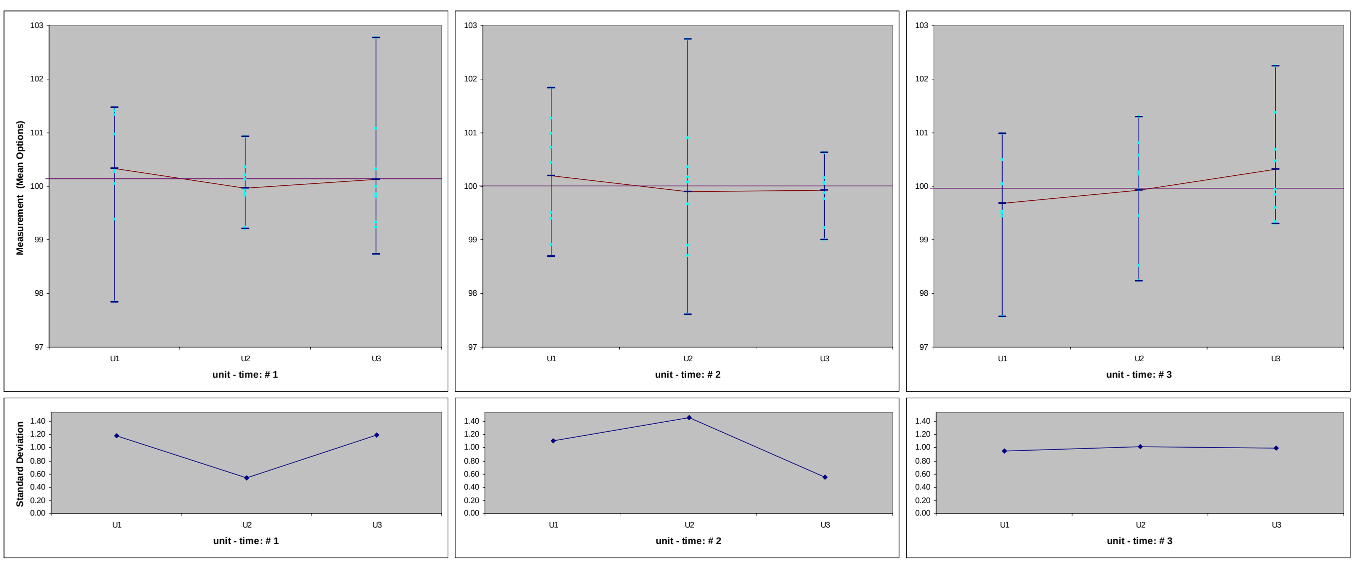
4. Check Use Entire Data Table. Click Next.

5. Note that the input X's can be text or numeric but should be discrete. Y's must be numeric - typically continuous, but can also be count or proportion data.

6. Select Measurement as the Numeric Response (Y); unit as Group Category (X1) and time as Group Category (X2)



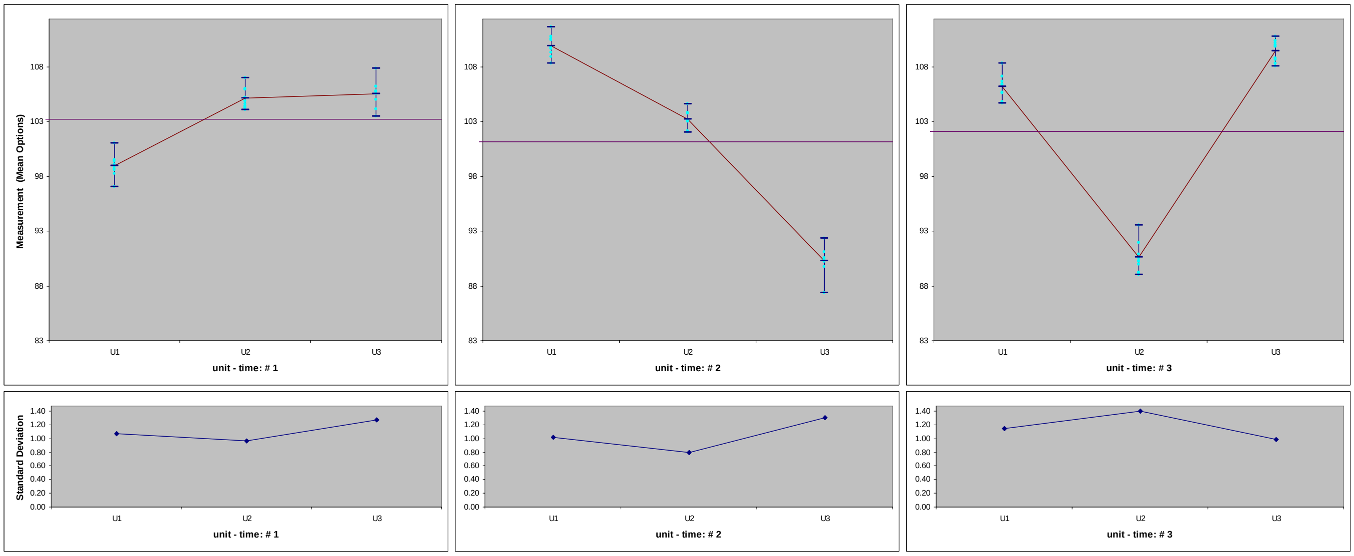
7. Click OK. Resulting Multi-Vari Chart illustrating dominant "Within Unit" Source of Variation:



8. Open **Between.xls**, click Sheet 1. Select SigmaXL > Graphical Tools > Multi-Vari Charts. Check Use Entire Data Table. Click Next.

9. Select Measurement as the Numeric Response (Y); unit as Group Category (X1) and time as Group Category (X2).

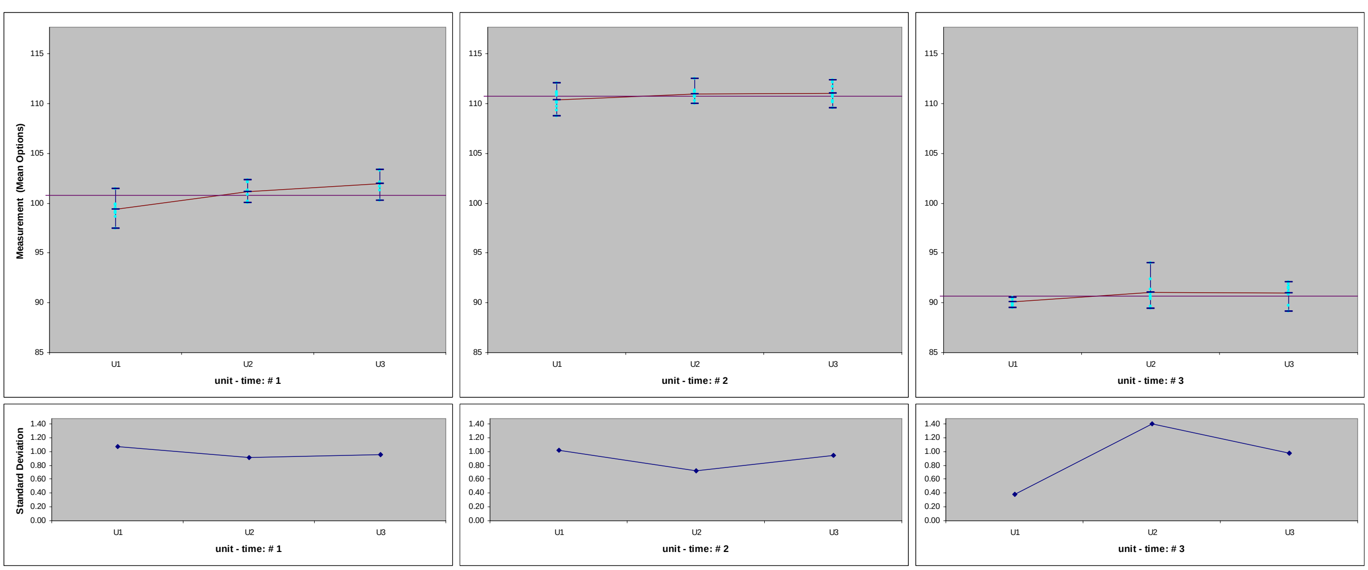
10. Click OK. Resulting Multi-Vari Chart illustrating dominant "Between Unit" Source of Variation:



11. Open **OverTime.xls**, click Sheet 1. Select SigmaXL > Graphical Tools > Multi-Vari Charts. Check Use Entire Data Table. Click Next.

12. Select Measurement as the Numeric Response (Y); unit as Group Category (X1) and time as Group Category (X2).

13. Click OK. Resulting Multi-Vari Chart illustrating dominant "Over Time" Source of Variation:



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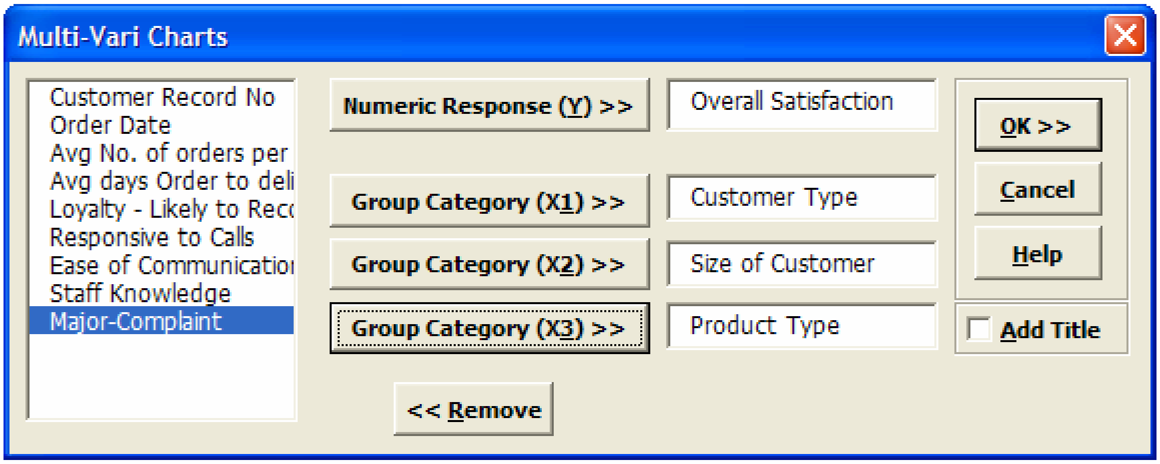
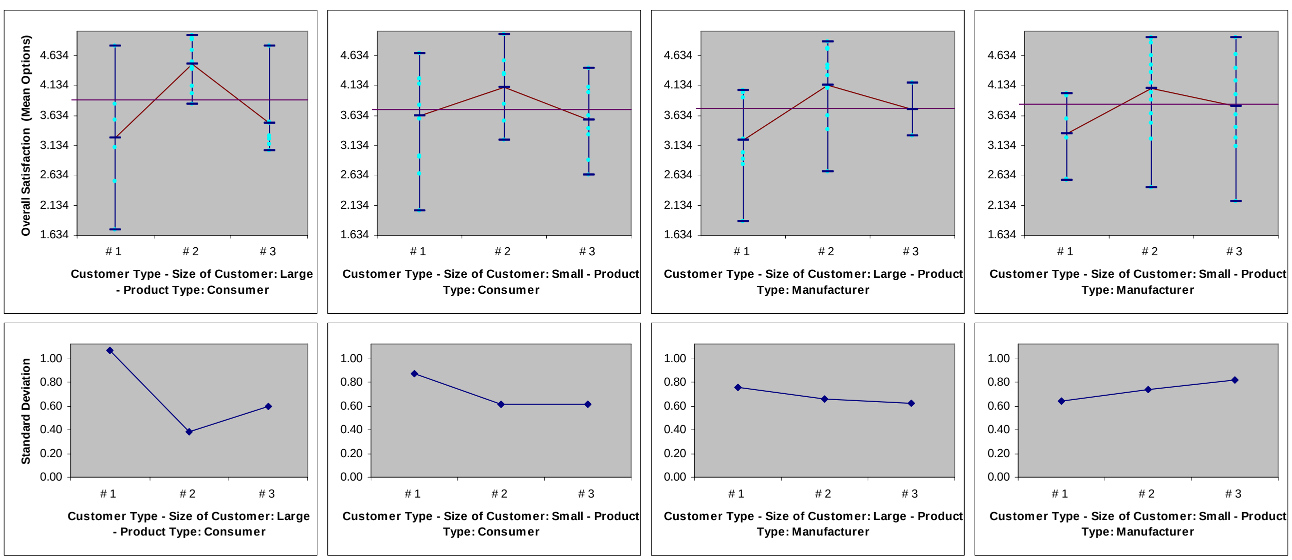
14. Open **Customer Data.xls**, click Sheet 1. Select SigmaXL > Graphical Tools > Multi-Vari Charts

15. Select Overall Satisfaction as Y; Customer Type as X1; Size of Customer as X2; Product Type as X3.



16. Click OK. Resulting Multi-Vari chart:



Examining this Multi-Vari chart reveals that the dominant Source of Variation is “within” Customer Type, followed by “between” Customer Type. Furthermore, it would be worthwhile to examine the combination of Customer Type 2, Customer Size Large, and Product Type Consumer.

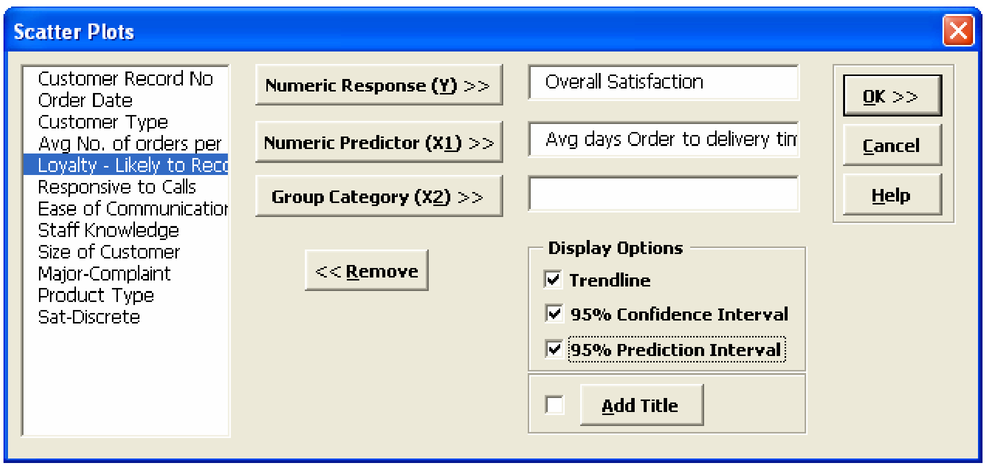
Other tools that can help us identify potential X factors that may explain some of the large “Within” variability are the Scatter Plot, Scatter Plot Matrix and Correlation Matrix.

Part P – Scatter Plots

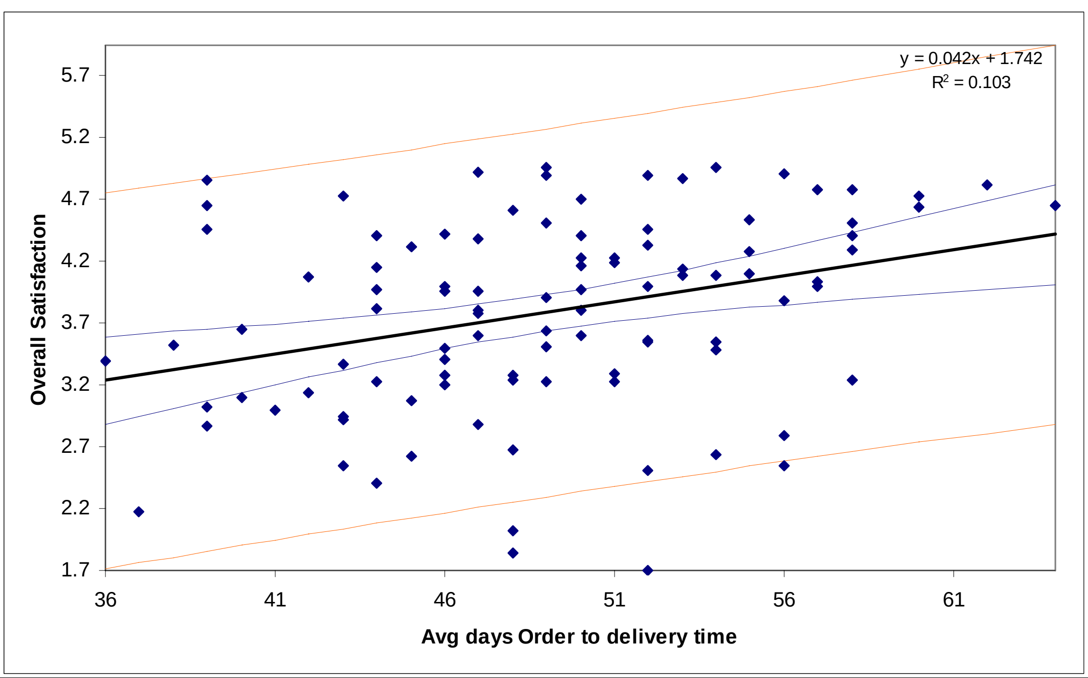
Scatter Plots

1. Open **Customer Data.xls**. Click Sheet 1 Tab. Click SigmaXL > Graphical Tools > Scatter Plots; if necessary, click Use Entire Data Table, click Next.

2. Select Overall Satisfaction as Y, Avg Days Order Time to Delivery as X1.



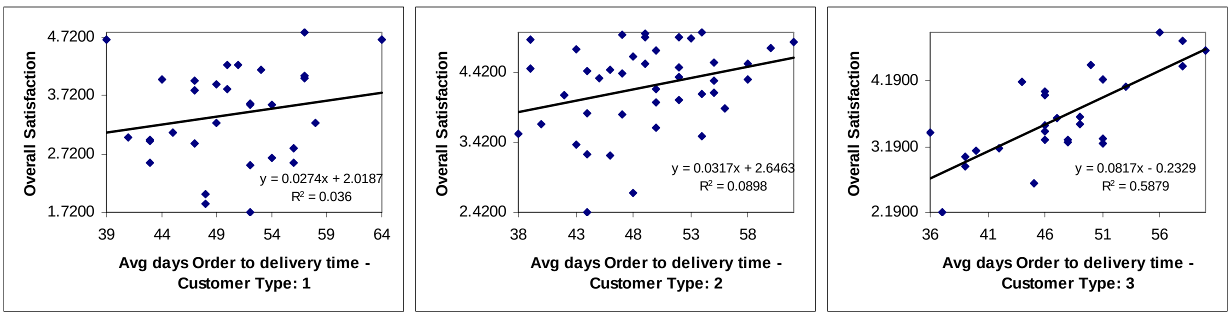
3. Click OK. The resulting Scatter Plot is shown with equation, trendline, 95% confidence interval (blue lines – for a given X value this is the 95% confidence interval for predicted mean Overall Satisfaction) and 95% prediction interval (red lines – for a given X value this is the 95% confidence interval for predicted individual values of Overall Satisfaction).



The equation is based on linear regression, using the method of least squares. R-squared * 100 is the percent variation of Y explained by X (here 10.3%).

4. Now we want to redo the Scatter Plot and stratify by Customer Type. Press **F3** or click "Recall SigmaXL Dialog" to recall last dialog. (or Click Sheet 1 Tab; Click SigmaXL > Graphical Tools > Scatter Plots; click Next).

5. Select Overall Satisfaction as Y, Average Days Order Time to Delivery as X1; Customer Type as X2, Uncheck 95% Confidence Interval and 95% Prediction Interval. Click OK. Resulting Scatter Plots are shown (with formulas moved and resized):



Clearly, according to the analysis, Customer Type 3 is happier if orders take longer! But, does this make sense? Of course not! Customer Sat scores should not increase with Order to Delivery time. What is happening here? This is a coincidental situation. Something else is driving customer satisfaction. We will now look at the Scatter Plot Matrix to help us investigate other factors influencing Customer Satisfaction.

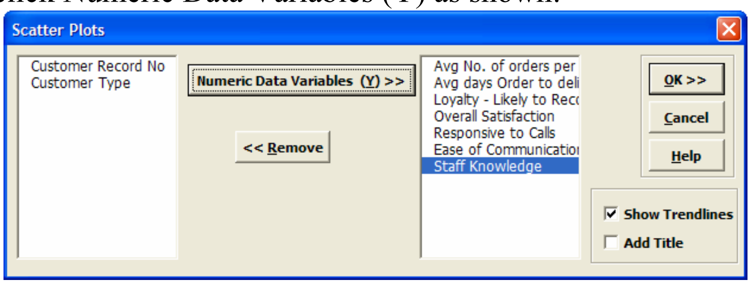
Tip: Be careful when interpreting scatter plots (and other statistical tools): Y versus X correlation or statistical significance does not always mean that we have a causal relationship. Umbrella sales are highly correlated to traffic accidents, but we cannot reduce the rate of traffic accidents by purchasing fewer umbrellas! The best way to validate a relationship is to perform a Design of Experiments (see Improve Phase).

Scatter Plot Matrix

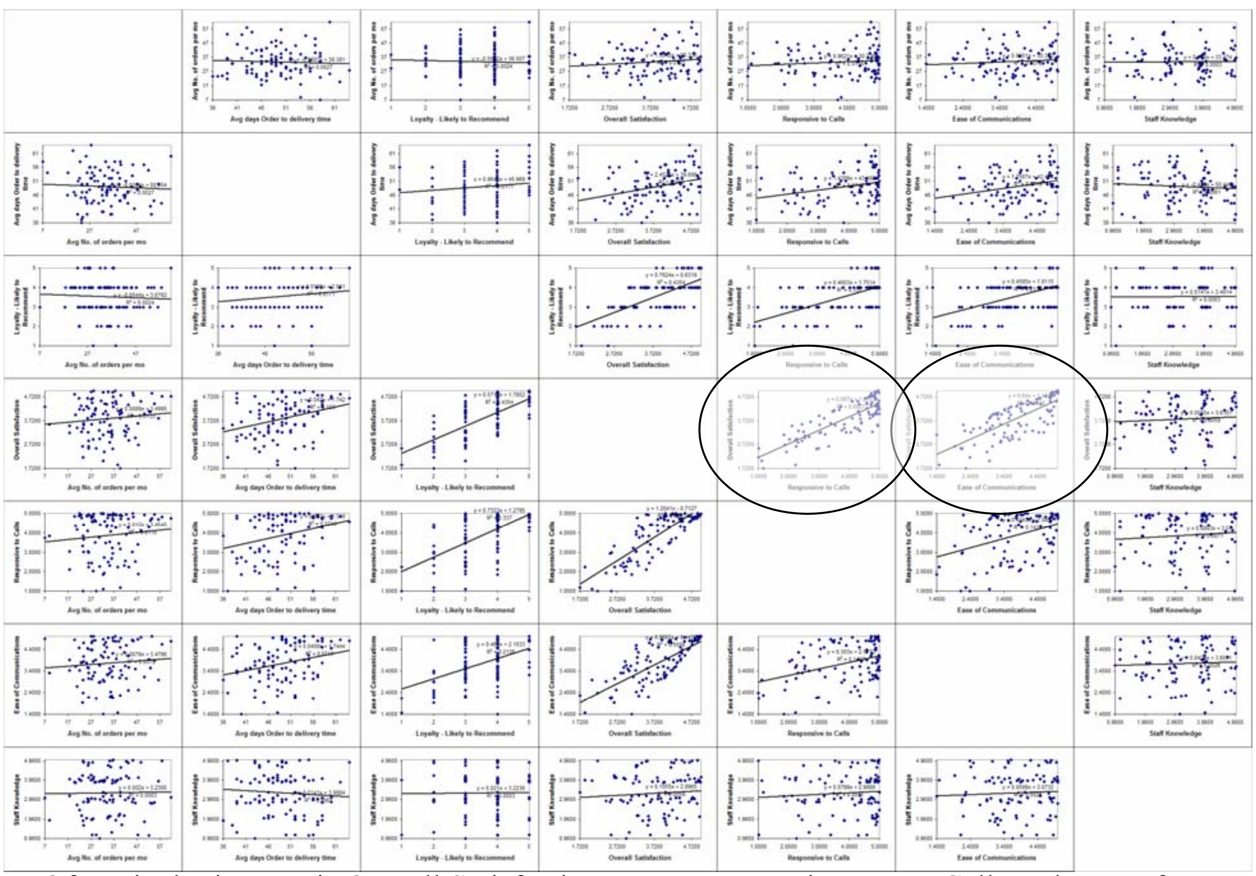
1. Click Sheet 1 Tab of **Customer Data.xls** (or press **F4** to activate last worksheet). Click SigmaXL > Graphical Tools > Scatter Plot Matrix.

2. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

3. Select the variable "Avg No of orders per month"; shift-click on "Staff Knowledge" and click Numeric Data Variables (Y) as shown:



4. Click OK. Resulting Scatter Plot Matrix:



Of particular interest is Overall Satisfaction versus Responsiveness to Calls and Ease of Communications. These will be explored further with Multiple Linear Regression.

Part Q – Correlation Matrix

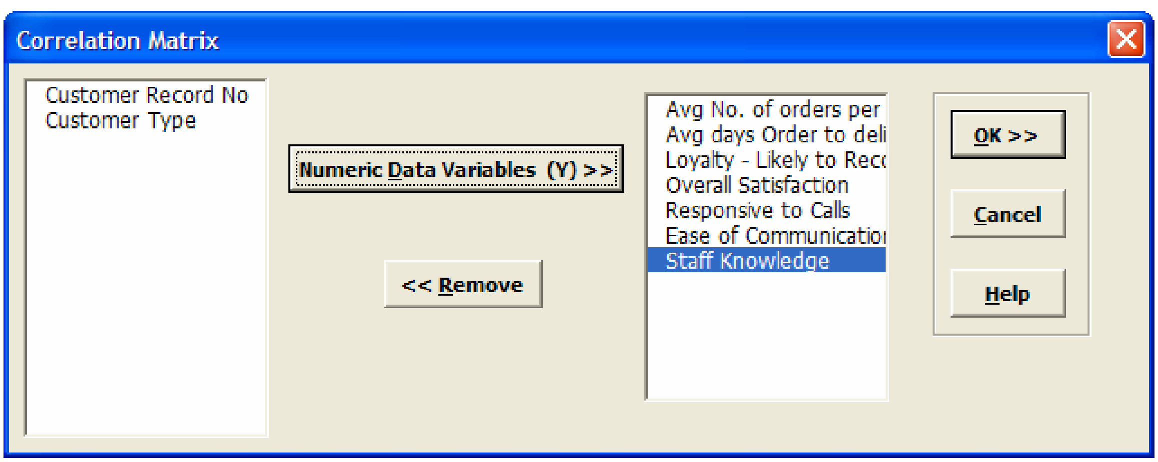
The correlation matrix complements the scatterplot matrix by quantifying the degree of association. The following table shows the approximate relationship between r, R-squared, and degree of association:

Pearson Correlation Coefficient (r)	R-Squared (%)	Degree of association
0.9 <= |r| <=1	> 80 %	Strong
0.7 <= |r| < 0.9	50 % to 80 %	Moderate
|r| < 0.7	< 50 %	Weak
Pearson Probability, p > 0.05		None

Correlation Matrix

1. Open **Customer Data.xls**. Click Sheet 1 tab (or press **F4** to activate last worksheet). Click SigmaXL > Statistical Tools > Correlation Matrix. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

2. Select the variable "Avg No of orders per month"; shift-click on "Staff Knowledge" and click Numeric Data Variables (Y) as shown:



3. Click OK. Resulting Correlation Matrix is shown:

Pearson Correlations	Avg No. of orders per mo	Avg days Order to delivery time	Loyalty - Likely to Recommend	Overall Satisfaction	Responsive to Calls	Ease of Communications	Staff Knowledge
Avg No. of orders per mo	1.0000	-0.0518	-0.0491	0.1155	0.1076	0.0885	0.0186
Avg days Order to delivery time		1.0000	0.1307	0.3210	0.2725	0.2681	-0.0781
Loyalty - Likely to Recommend			1.0000	0.6599	0.5805	0.4622	0.0176
Overall Satisfaction				1.0000	0.8262	0.7454	0.0766
Responsive to Calls					1.0000	0.3791	0.0845
Ease of Communications						1.0000	0.0506
Staff Knowledge							1.0000

Pearson Probabilities	Avg No. of orders per mo	Avg days Order to delivery time	Loyalty - Likely to Recommend	Overall Satisfaction	Responsive to Calls	Ease of Communications	Staff Knowledge
Avg No. of orders per mo		0.6090	0.6279	0.2527	0.2865	0.3812	0.8541
Avg days Order to delivery time			0.1949	0.0011	0.0061	0.0070	0.4398
Loyalty - Likely to Recommend				0.0000	0.0000	0.0000	0.8622
Overall Satisfaction					0.0000	0.0000	0.4490
Responsive to Calls						0.0001	0.4035
Ease of Communications							0.6171
Staff Knowledge							

Spearman Rank Correlations	Avg No. of orders per mo	Avg days Order to delivery time	Loyalty - Likely to Recommend	Overall Satisfaction	Responsive to Calls	Ease of Communications	Staff Knowledge
Avg No. of orders per mo	1.0000	-0.0305	-0.0917	0.1006	0.0738	0.1000	0.0187
Avg days Order to delivery time		1.0000	0.1097	0.3407	0.2489	0.2613	-0.0828
Loyalty - Likely to Recommend			1.0000	0.6167	0.5507	0.4071	-0.0190
Overall Satisfaction				1.0000	0.7782	0.7509	0.0890
Responsive to Calls					1.0000	0.3204	0.0895
Ease of Communications						1.0000	0.0716
Staff Knowledge							1.0000

Spearman Rank Probabilities	Avg No. of orders per mo	Avg days Order to delivery time	Loyalty - Likely to Recommend	Overall Satisfaction	Responsive to Calls	Ease of Communications	Staff Knowledge
Avg No. of orders per mo		0.7629	0.3644	0.3192	0.4655	0.3222	0.8532
Avg days Order to delivery time			0.2774	0.0005	0.0125	0.0087	0.4127
Loyalty - Likely to Recommend				0.0000	0.0000	0.0000	0.8513
Overall Satisfaction					0.0000	0.0000	0.3786
Responsive to Calls						0.0012	0.3758
Ease of Communications							0.4792
Staff Knowledge							

Correlations highlighted in red are considered significant (p-values < .05). The corresponding correlation coefficients above the p-values are also highlighted in red. (Compare these to the Scatterplot Matrix).

Note that Spearman's Rank Correlation complements Pearson's Correlation, in that it provides a robust measure of association. Spearman's rank is based on correlated ranks, which are not sensitive to outliers.

Part R – Multiple Regression

Multiple Regression

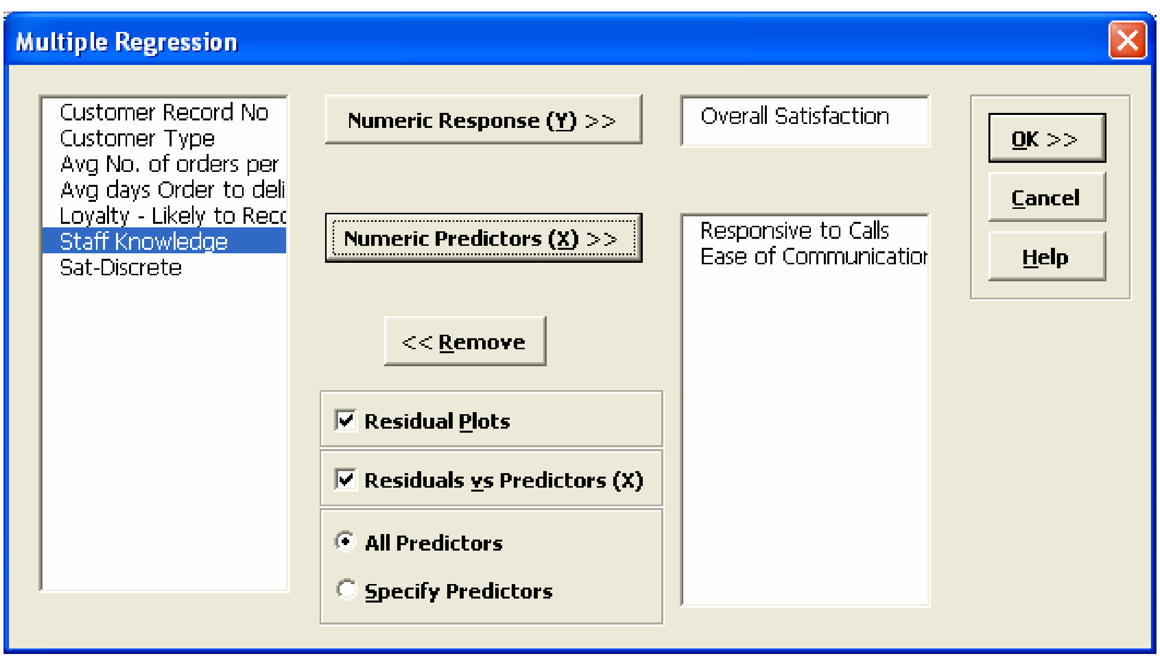
Multiple Regression analyzes the relationship between one dependent variable (Y) and multiple independent variables (X's). It is used to discover the relationship between the variables and create an empirical equation of the form:

Y = b0 + b1*X1 + b2*X2 + ... + bn*Xn

This equation can be used to predict a Y value for a given set of input X values. SigmaXL uses the method of least squares to solve for the model coefficients and constant term. Statistical tests of hypothesis are provided for the model coefficients.

1. Open **Customer Data.xls**. Click Sheet 1 Tab (or press **F4** to activate last worksheet). Click SigmaXL > Statistical Tools > Regression > Multiple Regression; if necessary, click Use Entire Data Table, click Next.

2. Select Overall Satisfaction as the Response (Y), select Responsive to Calls and Ease of Communications as the Predictors (X's).



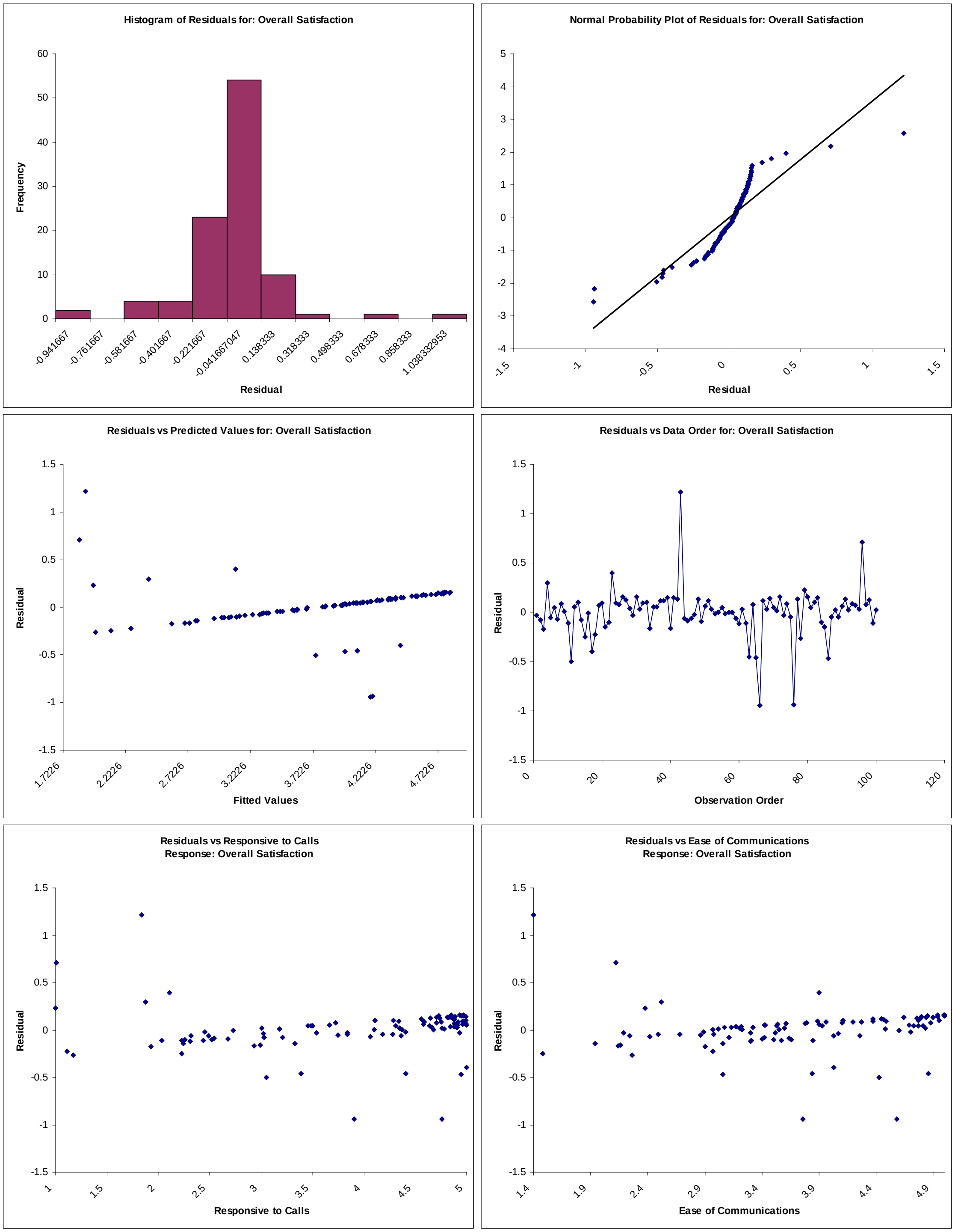
3. Click OK. Resulting Multiple Regression report is shown:

The Regression Equation is: Overall Satisfaction = (0.493463) + (0.435673) * Responsive to Calls + (0.433346) * Ease of Communications

Model Summary					
R-Sq	90.08%				
R-Sq (adj)	89.88%				
S	0.248942				
Analysis of Variance					
Source	**DF**	**SS**	**MS**	**F**	**P**
Model	2	54.60103	27.30052	440.5287603	2.11717E-49
Error	97	6.011299	0.061972		
Total	99	60.61233			
Predictor	**Coef**	**SE Coef**	**T**	**P**	
Constant	0.493463	0.116857	4.222801	5.44445E-05	
Responsive to Calls	0.435673	0.023711	18.37429	2.3518E-33	
Ease of Communications	0.433346	0.029667	14.60693	3.08751E-26	

This model of Overall Satisfaction as a function of Responsiveness to Calls and Ease of Communications looks very good with an R-Square value of 90%. Both Predictors are shown to be significant with their respective p-values < .05. Clearly we need to focus on these two X factors to improve customer satisfaction.

4. The Residual Plots are shown below:



Residuals are the unexplained variation from the regression model (Y - Y-hat). We expect to see the residuals normally distributed with no obvious patterns in the above graphs. Clearly this is not the case here, with the Residuals versus Predicted Values indicating there is likely some other X factor influencing the Overall Satisfaction. It would be appropriate to consider other factors in the model but we will not pursue this further.

Part S – Logistic Regression

Binary Logistic Regression

Binary Logistic Regression is used to analyze the relationship between one binary dependent variable (Y) and multiple independent numeric and/or discrete variables (X's). It is used to discover the relationship between the variables and create an empirical equation of the form:

Ln(Py/(1-Py)) = b0 + b1*X1 + b2*X2 + ... + bn*Xn

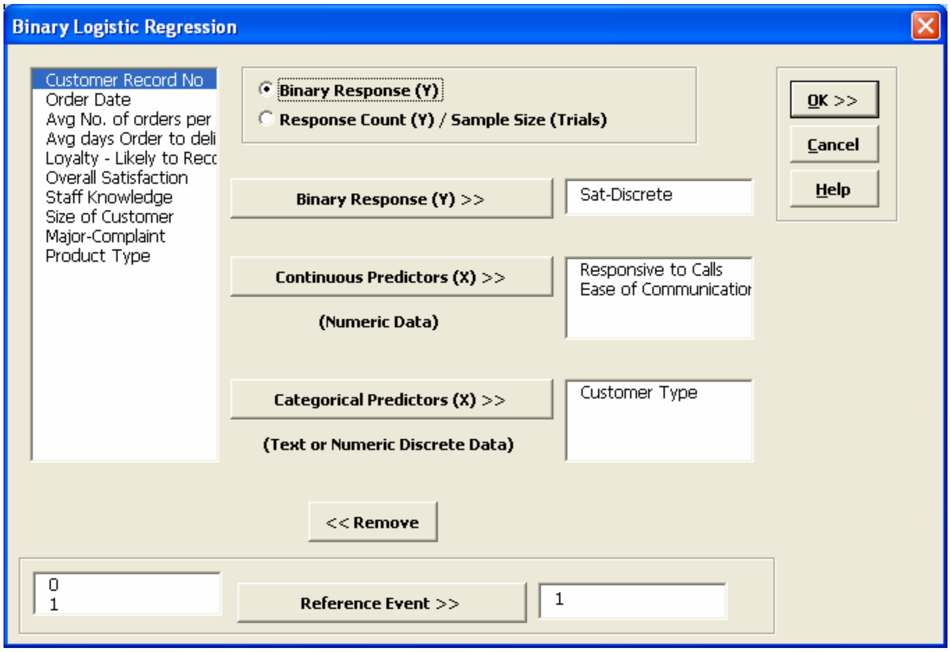
This equation can be used to predict an event probability Y value for a given set of input X values. SigmaXL uses the method of maximum likelihood to solve for the model coefficients and constant term. Statistical tests of hypothesis and odds-ratios are provided for the model coefficients. The odds-ratios identify change in likelihood of the event for one unit change in X.

An example application from medical research would be Y=Disease (Yes/No) and X's = Age, Smoker (Yes/No), Number Years of Smoking and Weight. The model coefficient p-values would indicate which X's are significant and the odds-ratios would provide the relative change in risk for each unit change in X.

We will analyze the familiar Customer Satisfaction data using Y=Discrete Satisfaction where the values have been coded such that an Overall Satisfaction score >= 3.5 is considered a 1, and scores < 3.5 are considered a 0. Please note, we are not advising that continuous data be converted to discrete data in actual practice, but simply using the Discrete Satisfaction score for continuity with the previous analysis.

1. Open **Customer Data.xls**. Click Sheet 1 Tab (or press **F4** to activate last worksheet). Click SigmaXL > Statistical Tools > Regression > Binary Logistic Regression; if necessary, click Use Entire Data Table, click Next.

2. Select Sat-Discrete as the 'Response (Y)', select Responsive to Calls and Ease of Communications as 'Continuous Predictors (X)' and Customer Type for 'Categorical Predictors (X)'.



Note that Response Count (Y)/Sample Size (Trials) should be used when each record contains both the number of occurrences along with associated sample size. This is common when tracking daily quality data or performing design of experiments where each run contains a response of the number of defects and sample size.

3. Click OK. The resulting Binary Logistic report is shown:

Binary Logistic Regression Model: ln(Py/(1-Py)) = (-16.647) + (2.4536) * Responsive to Calls + (2.3665) * Ease of Communications + (0.546091) * Customer Type_2 + (-1.1306) * Customer Type_3
Logit Link

Response Summary: Sat-Discrete

Value	Count	Proportion	Reference Event
0	33	0.33	
1	67	0.67	x
Total	100		

Parameter Estimates:

Term	Coefficient	SE Coefficient	Z	P	Odds Ratio	Lower 95% Odds Ratio	Upper 95% Odds Ratio
Constant	-16.647	3.8370	-4.3385	0.0000			
Responsive to Calls	2.4536	0.558680	4.3918	0.0000	11.63042223	3.890783966	34.76592952
Ease of Communications	2.3665	0.673794	3.5122	0.0004	10.660	2.8458	39.930
Customer Type_2	0.546091	1.08	0.507274	0.6120	1.7265	0.209320	14.240
Customer Type_3	-1.1306	0.990525	-1.1414	0.2537	0.322850	0.046328641	2.2498

Wald Estimates for Categorical (Discrete) Predictors:

Term	Chi-Square	DF	P
Customer Type	2.6297	2	0.2685

Model Summary and Goodness-of-Fit Statistics:

Log-Likelihood	-19.883
Test that all slope coefficients are equal to zero:	
Likelihood Ratio Chi-Square (G)	87.070
DF	4
P-Value	0.0000
McFadden's Pseudo R-Square	68.65%

Observed and Predicted Outcomes:

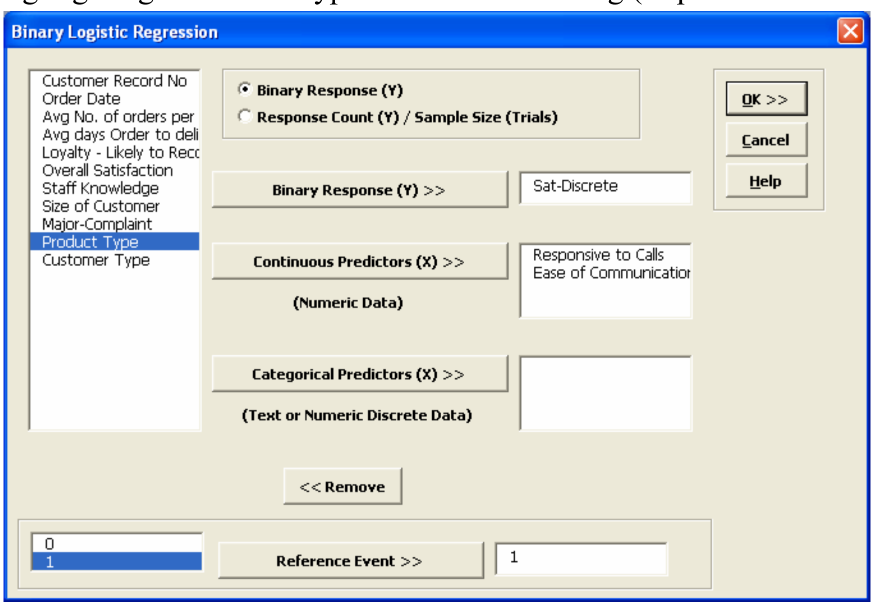
Observed Outcome	Predicted Outcome Ŷ = 0	Predicted Outcome Ŷ = 1	Row Total
Y = 0	29	4	33
Y = 1	3	64	67
Column Total	32	68	100
Percent Correctly Predicted:	93.00%		

4. The Likelihood Ratio p-value < .05 tells us that the model is significant. The p-values for the coefficients in the Parameter Estimates table confirm that Responsive to Calls and Ease of Communications are significant.

5. The p-value in Wald Estimates for Categorical (Discrete) Predictors table tells us that Customer Type is not significant here.
   Tip: Significance for categorical predictors should be based on the Wald Estimates not the p-values given in the Parameter Estimates table.

6. Note that Customer Type 1 is not displayed in the Parameter Estimates table. This is the "hidden" reference value for Customer Type. Categorical predictors must have one level selected as a reference value. SigmaXL sorts the levels alphanumerically and selects the first level as the reference value.

7. Now we will rerun the binary logistic regression but remove Customer Type as a predictor. Press **F3** or click "Recall SigmaXL Dialog" to recall last dialog. Remove Customer Type by highlighting Customer Type and double-clicking (or press the Remove button).



8. Click Ok. The resulting Binary Logistic report is shown:

Binary Logistic Regression Model: ln(Py/(1-Py)) = (-17.703) + (2.4617) * Responsive to Calls + (2.5888) * Ease of Communications
Logit Link

Response Summary: Sat-Discrete

Value	Count	Proportion	Reference Event
0	33	0.33	
1	67	0.67	x
Total	100		

Parameter Estimates:

Term	Coefficient	SE Coefficient	Z	P	Odds Ratio	Lower 95% Odds Ratio	Upper 95% Odds Ratio
Constant	-17.703	3.9466	-4.4855	0.0000			
Responsive to Calls	2.4617	0.559872	4.3970	0.0000	11.72530911	3.913379113	35.13149883
Ease of Communications	2.5888	0.668691	3.8714	0.0001	13.313	3.5899	49.372

Model Summary and Goodness-of-Fit Statistics:

Log-Likelihood	-21.275
Test that all slope coefficients are equal to zero:	
Likelihood Ratio Chi-Square (G)	84.285
DF	2
P-Value	0.0000
McFadden's Pseudo R-Square	66.45%
Goodness-of-Fit Tests (P-Value < .05 indicates Lack-of-Fit):	
Pearson Residuals Chi-Square	112.63
DF	97
P-Value	0.1326
Deviance Residuals Chi-Square	42.551
DF	97
P-Value	1.0000
Hosmer-Lemeshow Chi-Square	20.186
DF	8
P-Value	0.0097
Measures of Association:	
Concordant	2123
Discordant	88
Ties	0
Total	2211
Concordant Percent	96.02
Discordant Percent	3.98
Ties Percent	0.00
Goodman-Kruskal Gamma	0.920398
Somers' D	0.920398
Kendall's Tau-a	0.411111

Observed and Predicted Outcomes:

Observed Outcome	Predicted Outcome		Row Total
	Ŷ = 0	Ŷ = 1	
Y = 0	30	3	33
Y = 1	1	66	67
Column Total	31	69	100
Percent Correctly Predicted:	96.00%		

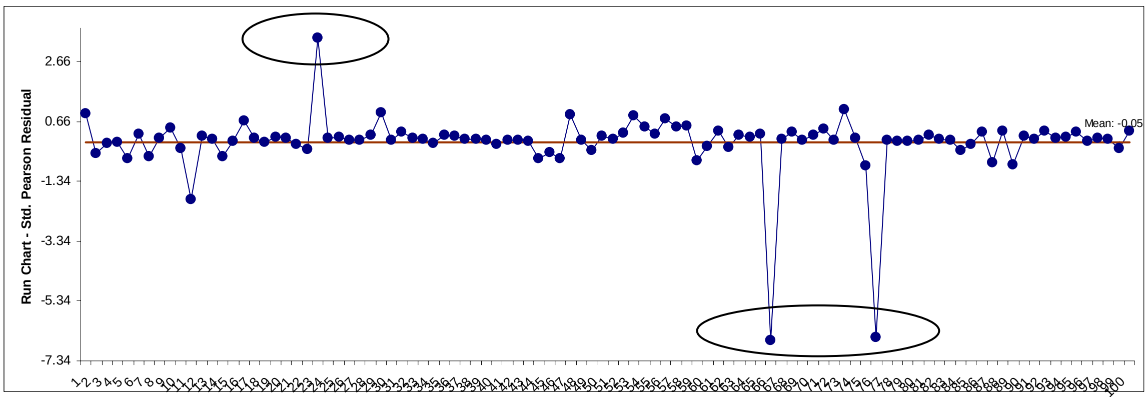
9. The Odds Ratios in the Parameter Estimates table tell us that for every unit increase in Responsive to Calls we are 11.7 times more likely to obtain a satisfied customer. For every unit increase in Ease of Communications we are 13.3 times more likely to obtain a satisfied customer.

10. McFadden's Pseudo R-Square mimics the R-square found in linear regression. This value varies between 0 and 1 but is typically much lower than the traditional R-squared value. A value less than 0.2 indicates a weak relationship; 0.2 to 0.4 indicates a moderate relationship; greater than 0.4 indicates a strong relationship. Here we have an R-square value of 0.66 indicating a strong relationship. This is also confirmed with the Percent Correctly Predicted value of 96%.

11. The Pearson, Deviance and Hosmer-Lemeshow Goodness of Fit tests are used to confirm if the binary logit model fits the data well. P-values < .05 for any of these tests indicate a significant lack of fit. Here the Hosmer-Lemeshow test is indicating lack of fit. Residuals analysis will help us to see where the model does not fit the data well.

12. The measures of association are used to indicate the relationship between the observed responses and the predicted probabilities. Larger values for Goodman-Kruskal Gamma, Somers' D and Kendall's Tau-a indicate that the model has better predictive ability.

13. The residuals report is given on the Sheet **Binary Logistic Residuals**. Three types of residuals are provided: Pearson, Standardized Pearson and Deviance. The Standardized Pearson Residual is most commonly used and is shown here plotted on a Run Chart:



Any Standardized Pearson Residual value that is less than -3 or greater than +3 are considered extreme and should be investigated. There are 3 such outliers here: rows 24, 67, and 77 in the residuals table. The +3.4 value indicates that the predicted event probability was low (.08) but the actual result was a 1. The -6.6 value indicates that the predicted event probability was high (.98) but the actual result was a 0. The large negative residuals have high Responsive to Calls and Ease of Communications but dissatisfied customers. The reasons for these discrepancies should be explored further but we will not do so here.

14. Reselect the Binary Logistic report sheet. Scroll over to display the event probability calculator:

Response Event Probability:

Predictors	Enter Settings:	Predicted Event Probability
Responsive to Calls		
Ease of Communications		

This calculator provides a predicted event probability for given values of X (in this case the probability of a satisfied customer). Enter the values 3,3; 4,4; 5,5 as shown:

Response Event Probability:

Predictors	Enter Settings:	Predicted Event Probability
Responsive to Calls	3	0.072339563
Ease of Communications	3	

Response Event Probability:

Predictors	Enter Settings:	Predicted Event Probability
Responsive to Calls	4	0.924086245
Ease of Communications	4	

Response Event Probability:

Predictors	Enter Settings:	Predicted Event Probability
Responsive to Calls	5	0.999474014
Ease of Communications	5	

If Responsive to Calls and Ease of Communications are both equal to 3, the probability of a satisfied customer is only .07 (7%); if Responsive to Calls and Ease of Communications are both equal to 5, the probability of a satisfied customer is .9995 (99.95%)

15. Note that if the calculator includes predictors that are categorical (discrete), enter a 0 or 1 to denote the selected level as shown below (using the original analysis which included Customer Type):

Response Event Probability:

Predictors	Enter Settings:	Predicted Event Probability
Responsive to Calls	3.02	0.71922567
Ease of Communications	4.07	
Customer Type_2	1	
Customer Type_3	0	

If we wanted to select Customer Type 1, enter a 0 for both Customer Types 2 and 3. Customer Type 1 is the hidden reference value.

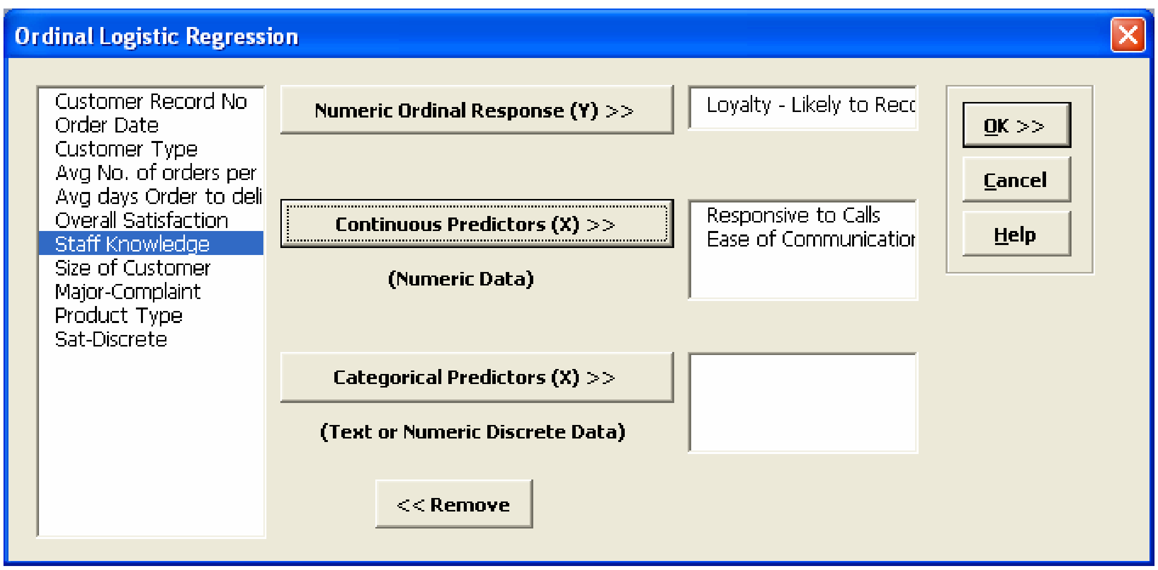
Ordinal Logistic Regression

Ordinal Logistic Regression is used to analyze the relationship between one ordinal dependent variable (Y) and multiple independent continuous and/or discrete variables (X's).

We will analyze the Customer Satisfaction data using Y=Loyalty –Likely to Recommend Score which contains ordinal integer values from 1 to 5, where 5 indicates that the customer is very likely to recommend us and a 1 indicating that they are very likely to not recommend us.

1. Open **Customer Data.xls**. Click Sheet 1 Tab (or press **F4** to activate last worksheet). Click SigmaXL > Statistical Tools > Regression > Ordinal Logistic Regression; if necessary, click Use Entire Data Table, click Next.

2. Select Loyalty – Likely to Recommend as the Response (Y), select Responsive to Calls and Ease of Communications as the Continuous Predictors (X's).



3. Click OK. The resulting Ordinal Logistic report is shown:

Ordinal Logistic Regression Model: ln(Py/(1-Py)) = Constant + (-1.01) * Responsive to Calls + (-0.790028) * Ease of Communications
Logit Link

Response Summary: Loyalty - Likely to Recommend

Value	Count	Proportion
1	2	0.02
2	10	0.1
3	33	0.33
4	43	0.43
5	12	0.12
Total	100	

Parameter Estimates:

Term	Coefficient	SE Coefficient	Z	P	Odds Ratio	Lower 95% Odds Ratio	Upper 95% Odds Ratio
Constant 1	1.6606	1.11	1.4956	0.1348			
Constant 2	4.1382	1.05	3.9435	0.0001			
Constant 3	6.7207	1.1985	5.6075	0.0000			
Constant 4	9.5189	1.3506	7.0479	0.0000			
Responsive to Calls	-1.01	0.208727	-4.8451	0.0000	0.363743	0.241614	0.547604
Ease of Communications	-0.790028	0.253998	-3.1104	0.0019	0.453832	0.275860	0.746624

Model Summary and Goodness-of-Fit Statistics:

Log-Likelihood	-105.24
Test that all slope coefficients are equal	
Likelihood Ratio Chi-Square (G)	47.850
DF	2
P-Value	0.0000
McFadden's Pseudo R-Square	0.185221
Goodness-of-Fit Tests	
Pearson Residuals Chi-Square	279.41
DF	394
P-Value	1.0000
Deviance Residuals Chi-Square	210.49
DF	394
P-Value	1.0000
Measures of Association:	
Concordant	2703
Discordant	693
Ties	11
Total	3407
Concordant Percent	79.337
Discordant Percent	20.340
Ties Percent	0.322865
Goodman-Kruskal Gamma	0.591873
Somers' D	0.589962
Kendall's Tau-a	0.406061

Observed and Predicted Outcomes:

Observed Outcome	Predicted Outcomes					
	Y = 1	Y = 2	Y = 3	Y = 4	Y = 5	Row Total
Y = 1	0	2	0	0	0	2
Y = 2	0	2	6	2	0	10
Y = 3	0	2	14	17	0	33
Y = 4	0	1	10	32	0	43
Y = 5	0	0	0	12	0	12
Column Total	0	7	30	63	0	100
Percent Correctly Predicted:	48.00%					

4. The Likelihood Ratio p-value < .05 tells us that the model is significant. The low p-values for the coefficients confirm that Responsive to Calls and Ease of Communications are significant.

5. The Odds Ratios tell us that for every one-unit increase in Responsive to Calls the chance of a Loyalty score of 1 versus 2 (or 2 versus 3, etc.) is reduced by a multiple of 0.36. This is not very intuitive but will be easy to see when we use the Response Outcome Probability calculator.

6. McFadden's Pseudo R-Square value is 0.185 indicating that this is a weak (but close to moderate) degree of association. This is also confirmed with the Percent Correctly Predicted value of 48%.

7. The Pearson and Deviance Goodness of Fit (GOF) tests are used to confirm if the ordinal logit model fits the data well. P-values < .05 would indicate a significant lack of fit. Given that the GOF p-values are greater than .05, we conclude that there is no significant lack of fit.

8. Scroll across to the Response Outcome Probability calculator. This calculator provides predicted outcome (event) probabilities for given values of X (in this case the probability of a satisfied customer). Enter the values 3,3; 4,4; 5,5 as shown:

Response Outcome Probability:

Predictors	Enter Settings:	Outcome	Predicted Cumulative Probability	Predicted Probability for each Level
Responsive to Calls	3	1	0.023126561	0.023126561
Ease of Communications	3	2	0.219975509	0.196848949
		3	0.788637917	0.568662408
		4	0.983934641	0.195296724
		5	1	0.016065359

Response Outcome Probability:

Predictors	Enter Settings:	Outcome	Predicted Cumulative Probability	Predicted Probability for each Level
Responsive to Calls	4	1	0.003892856	0.003892856
Ease of Communications	4	2	0.044482997	0.040590141
		3	0.381166061	0.336683064
		4	0.909993674	0.528827613
		5	1	0.090006326

Response Outcome Probability:

Predictors	Enter Settings:	Outcome	Predicted Cumulative Probability	Predicted Probability for each Level
Responsive to Calls	5	1	0.000644721	0.000644721
Ease of Communications	5	2	0.007626413	0.006981693
		3	0.092294263	0.08466785
		4	0.625327043	0.53303278
		5	1	0.374672957

9. Referring to the Predicted Probability for each Level, if Responsive to Calls and Ease of Communications are both equal to 3, we would expect to see typical loyalty scores of 3 (57%) with some at 2 (20%) and 4 (20%); if Responsive to Calls and Ease of Communications are both equal to 5, we would expect typical loyalty scores of 4 (53 %) with some at 3 (34%) and 5 (9%).

SigmaXL: Improve Phase Tools: Design of Experiments (DOE)

Part A – Overview of Basic Design of Experiments (DOE) Templates

The DOE templates are similar to the other SigmaXL templates: simply enter the inputs and resulting outputs are produced immediately. The DOE templates provide common 2-level designs for 2 to 5 factors. (Currently these templates do not allow the addition of center-points).

Click SigmaXL > Basic DOE Templates to access these templates:

- Two-Factor, 4-Run, Full-Factorial
- Three-Factor, 4-Run, Half-Fraction, Res III
- Three-Factor, 8-Run, Full-Factorial
- Four-Factor, 8-Run, Half-Fraction, Res IV
- Four-Factor, 16-Run, Full-Factorial
- Five-Factor, 8-Run, Quarter-Fraction, Res III
- Five-Factor, 16-Run, Half-Fraction, Res V

After entering the template data, main effects and interaction plots may be created by clicking SigmaXL > Basic DOE Templates > Main Effects & Interaction Plots. The DOE template must be the active worksheet.

DOE Templates are protected worksheets by default, but this may be modified by clicking Tools > Protection > Unprotect Sheet.

Advanced analysis is available, but this requires that you unprotect the DOE worksheet. The following example shows how to use Excel's Equation Solver and SigmaXL's Multiple Regression in conjunction with a DOE template.

Caution: If you unprotect the worksheet do not change the worksheet title (e.g. **Three-Factor, Two-Level, 8-Run, Full-Factorial Design of Experiments).** This title is used by the Main Effects & Interaction Plots to determine appropriate analysis. Also, do not modify any cells with formulas.

Part B – Three Factor Full Factorial Example

1. Open the file **DOE Example - Robust Cake.xls**. This is a Robust Cake Experiment adapted from the Video "Designing Industrial Experiments", by Box, Bisgaard and Fung.

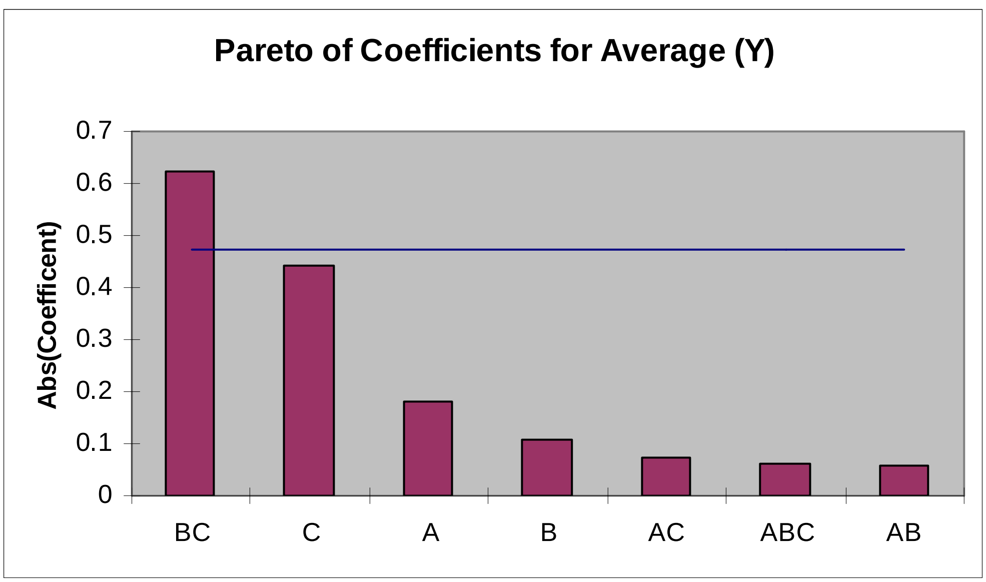
2. The response is Taste Score (on a scale of 1-7 where 1 is "awful" and 7 is "delicious").

3. The five Outer Array Reps have different Cooking Time and Temperature Conditions.

4. The goal is to Maximize Mean and Minimize StDev of the Taste Score.

5. The X factors are Flour, Butter, and Egg. Actual low and high settings are not given in the video, so we will use coded -1 and +1 values. We are looking for a combination of Flour, Butter, and Egg that will not only taste good, but consistently taste good over a wide range of Cooking Time and Temperature conditions.

6. Scroll down to view the Pareto of Abs. Coefficients for Average (Y).



7. The BC (Butter * Egg) interaction is clearly the dominant factor. The bars above the 95% confidence blue line indicate the factors that are statistically significant; in this case only BC is significant. Keep in mind that this is an initial analysis. Later, we will show how to do a more powerful Multiple Regression analysis on this data. (Also the Rule of Hierarchy states that if an interaction is significant, we must include the main effects in the model used).

8. The significant BC interaction is also highlighted in red in the table of Effects and Coefficients:

Calculation of Effects and Coefficients for Average (Y):

	Constant	A	B	C	AB	AC	BC	ABC
Avg(Avg(Y)) @ +1:		4.865	4.79	5.125	4.74	4.755	4.06	4.62
Avg(Avg(Y)) @ -1:		4.5	4.575	4.24	4.625	4.61	5.305	4.745
Effect (Delta):		0.365	0.215	0.885	0.115	0.145	-1.245	-0.125
Coefficient (Delta/2):	4.6825	0.1825	0.1075	0.4425	0.0575	0.0725	-0.6225	-0.0625
SE Coefficient:	0.2325	0.2325	0.2325	0.2325	0.2325	0.2325	0.2325	0.2325
T-value	20.1397849	0.7849	0.4624	1.9032	0.24731	0.31183	-2.6774	-0.2688
P-value	9.6928E-20	0.4383	0.6469	0.066	0.80625	0.75719	0.01161	0.7898

9. The R-Square value is given as 27%. This is very poor for a Designed Experiment. Typically we would like to see a minimum of 50%, with > 80% desirable.

R-Square:	27.03%
R-Square Adj.:	11.06%
S	1.4705

The reason for the poor R-square value is the wide range of values over the Cooking Temperature and Time conditions. In a robust experiment like this, it is more appropriate to analyze the mean response as an individual value rather than as five replicate values. The Standard Deviation as a separate response will also be of interest.

10. If the Responses are replicated, SigmaXL draws the blue line on the Pareto Chart using an estimate of experimental error from the replicates. If there are no replicates, an estimate called Lenth's Pseudo Standard Error is used.

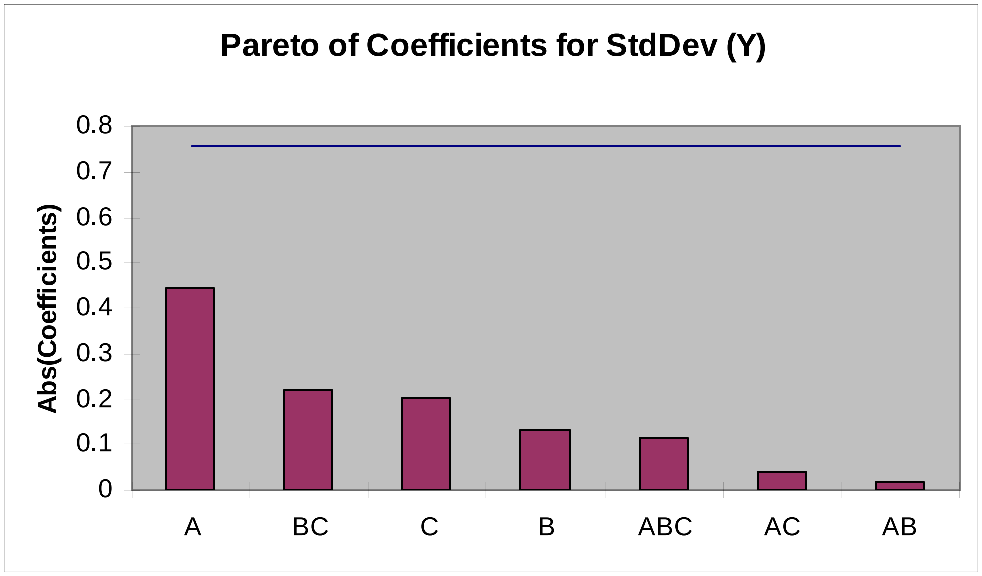
11. If the 95% Confidence line for coefficients were to be drawn using Lenth's method, the value would be 0.409 as given in the table:

Lenth's Pseudo Standard Error (PSE) Analysis for Unreplicated Data:

Lenth's PSE for Coefficients:	0.10875
Length's Margin of Error for Coefficients (95% Conf. Level):	0.40935
Length's Margin of Error for Effects (95% Conf. Level):	0.8187

This would show factor C as significant.

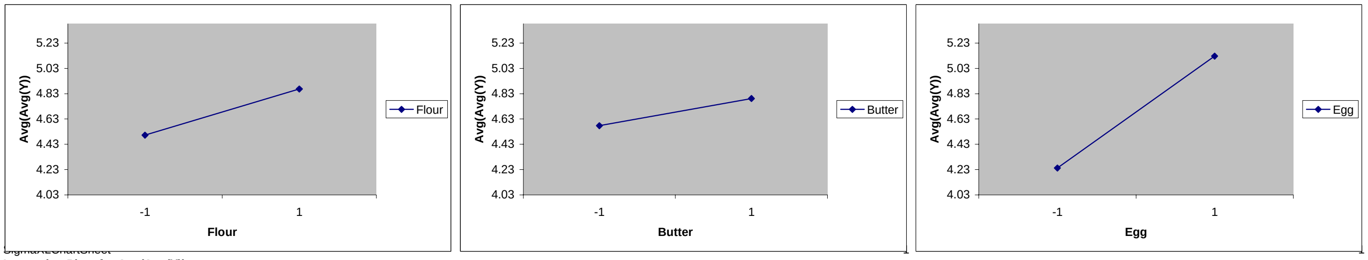
12. Scroll down to view the Pareto of Coefficients for StdDev(Y).



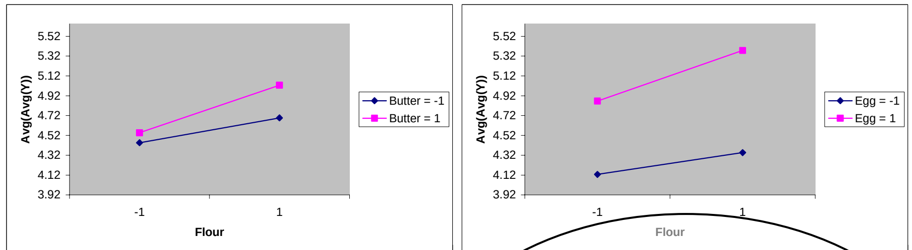
13. The A (Flour) main effect is clearly the dominant factor, but it does not initially appear to be statistically significant (based on Lenth's method). Later, we will show how to do a more powerful Regression analysis on this data.

14. The Pareto chart is a powerful tool to display the relative importance of the main effects and interactions, but it does not tell us about the direction of influence. To see this, we must look at the main effects and interaction plots. Click SigmaXL > Basic DOE Templates > Main Effects & Interaction Plots. The resulting plots are shown below:

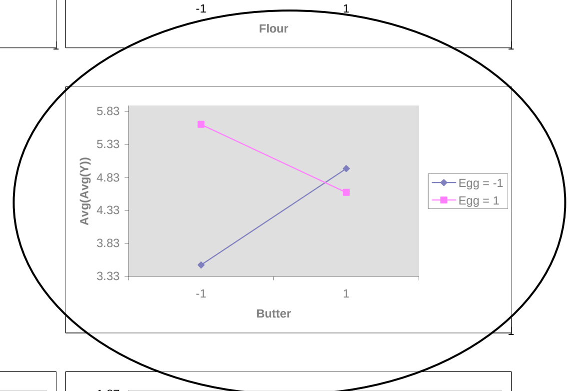
Main Effects Plots for Avg(Avg(Y))
Response: Taste Score (Scale 1-7 where 1 is "awful" and 7 is "delicious"); Outer Array Reps have different Cooking Time and Temp Conditions



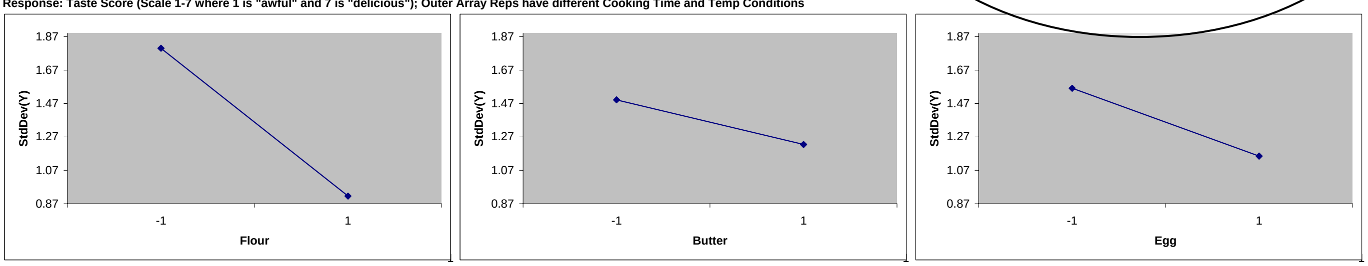
Interaction Plots for Avg(Avg(Y)):
Response: Taste Score (Scale 1-7 where 1 is "awful" and 7 is "delicious"); Outer Array Reps have different Cooking Time and Temp Conditions



Interaction Plots for Avg(Avg(Y)):
Response: Taste Score (Scale 1-7 where 1 is "awful" and 7 is "delicious"); Outer Array Reps have different Cooking Time and Temp Conditions



Main Effects Plots for StdDev (Y):
Response: Taste Score (Scale 1-7 where 1 is "awful" and 7 is "delicious"); Outer Array Reps have different Cooking Time and Temp Conditions



15. The Butter*Egg two-factor interaction is very prominent here. Looking at only the Main Effects plots would lead us to conclude that the optimum settings to maximize the average taste score would be Butter = +1, and Egg = +1, but the interaction plot tells a very different story. The correct optimum settings to maximize the taste score is Butter = -1 and Egg = +1.

16. Since Flour was the most prominent factor in the Standard Deviation Pareto, looking at the Main Effects plots for StdDev, we would set Flour = +1 to minimize the variability in taste scores. The significance of this result will be demonstrated using Regression analysis.

17. Click on the Sheet **Three-Factor 8-Run DOE**. At the Predicted Output for Y, enter Flour = 1, Butter = -1, Egg = 1 as shown:

Factor	Factor Name	Low	High
A	Flour	-1	1
B	Butter	-1	1
C	Egg	-1	1

Predicted Output for Y:

Factor Name	Enter Actual Factor Setting - uncoded	Factor setting coded	Y-hat:	S-hat:
	1	1	5.9	0.68191
	-1	-1		
	1	1		

The predicted average (Y-hat) taste score is 5.9 with a predicted standard deviation (S-hat) of 0.68. Note that this prediction equation includes all main effects, two-way interaction, and the three-way interaction.

Multiple Regression and Excel Solver (Advanced Topics):

18. In order to run Multiple Regression analysis we will need to unprotect the worksheet. Click Tools > Protection > Unprotect Sheet.

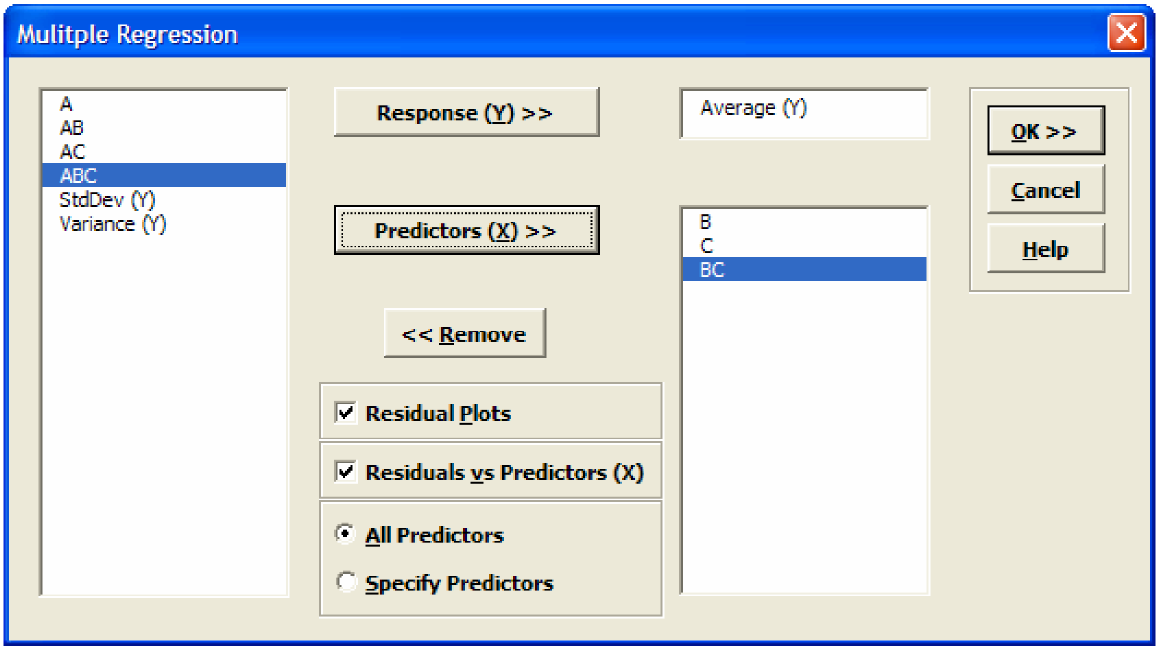
19. In the Coded Design Matrix, highlight columns A to ABC, and the calculated responses as shown:

Coded Design Matrix:

Standard Run Order	Actual Run Order	A	B	C	AB	AC	BC	ABC	Average (Y)	StdDev (Y)	Variance (Y)
1	6	-1	-1	-1	1	1	1	-1	3.52	2.4499	6.002
2	2	1	-1	-1	-1	-1	1	1	3.5	1.38022	1.905
3	7	-1	1	-1	-1	1	-1	1	4.74	1.47919	2.188
4	1	1	1	-1	1	-1	-1	-1	5.2	0.93541	0.875
5	5	-1	-1	1	1	-1	-1	1	5.38	1.45499	2.117
6	8	1	-1	1	-1	1	-1	-1	5.9	0.68191	0.465
7	3	-1	1	1	-1	-1	1	-1	4.36	1.81742	3.303
8	4	1	1	1	1	1	1	1	4.86	0.66558	0.443

20. Click SigmaXL > Statistical Tools > Regression > Multiple Regression. Click Next.

21. Select Average (Y) as the Response (Y); holding the CTRL key, select B, C, and BC; click Predictors (X) as shown:



22. Click OK. The resulting regression report is shown:

The Regression Equation is: Average (Y) = (4.6825) + (0.1075) * B + (0.4425) * C + (-0.6225) * BC

Model Summary

R-Sq	92.85%
R-Sq (adj)	87.50%
S	0.302572

Analysis of Variance

Source	**DF**	**SS**	**MS**	**F**	**P**
Model	3	4.75895	1.586317	17.3273257	0.009341
Error	4	0.3662	0.09155		
Total	7	5.12515			

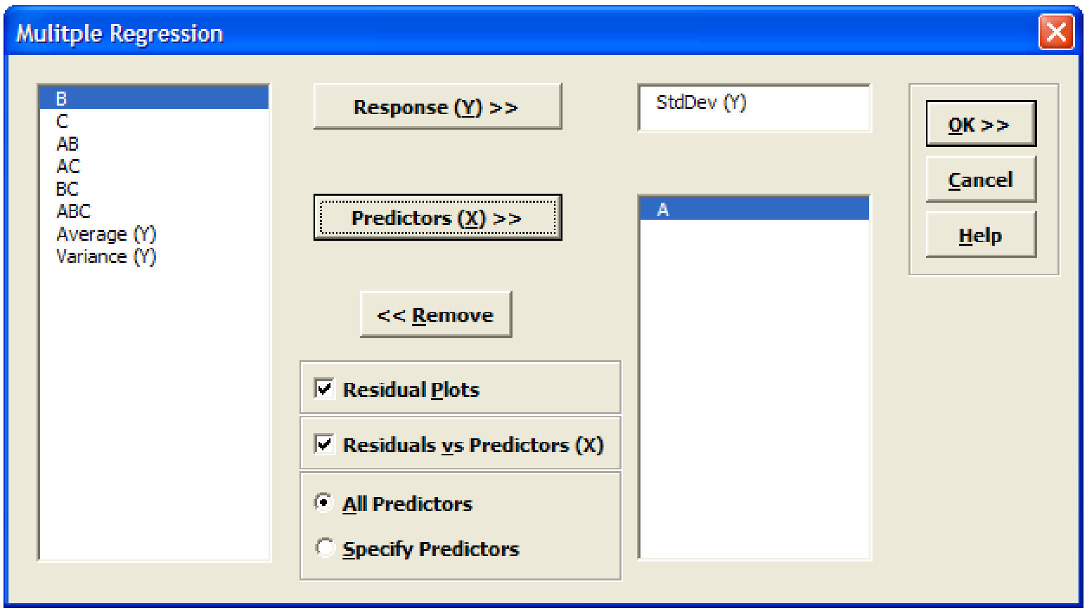
Predictor	**Coef**	**SE Coef**	**T**	**P**
Constant	4.6825	0.106975	43.77172	1.6288E-06
B	0.1075	0.106975	1.004903	0.371801
C	0.4425	0.106975	4.136463	0.01441791
BC	-0.6225	0.106975	-5.819091	0.00434233

Note that the R-square value of 92.85% is much higher than the earlier result of 27%. This is due to our modeling the mean response value rather than considering all data in the outer array. Note also that the C main effect now appears as significant.

23. Click on the Sheet **Three-Factor 8-Run DOE**.

24. With the Coded Design Matrix highlighted as before, click SigmaXL > Statistical Tools > Regression > Multiple Regression. Click Next.

25. Select StdDev (Y) as the Response (Y); select A for Predictors (X) as shown:



26. Click OK. Resulting regression report is shown:

The Regression Equation is: StdDev (Y) = (1.358077) + (-0.4423) * A

Model Summary	
R-Sq	61.54%
R-Sq (adj)	55.13%
S	0.403733

Analysis of Variance

Source	**DF**	**SS**	**MS**	**F**	**P**
Model	1	1.565009	1.565009	9.601252189	0.021155
Error	6	0.978003	0.163		
Total	7	2.543011			

Predictor	**Coef**	**SE Coef**	**T**	**P**
Constant	1.358077	0.142741	9.51426	7.68829E-05
A	-0.442296	0.142741	-3.098589	0.021154543

Note that Factor A (Flour) now shows as a statistically significant factor affecting the Standard Deviation of Taste Score.

27. Now we will use Excel's Equation Solver to verify the optimum settings determined using the Main Effects and Interaction Plots.

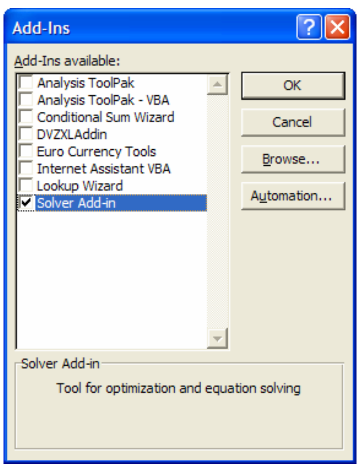
28. Click on the Sheet **Three-Factor 8-Run DOE**. At the Predicted Output for Y, enter 1 for Flour. We are setting this as a constraint, because Flour = +1 minimizes the Standard Deviation. Reset the Butter and Egg to 0 as shown:

Factor	Factor Name	Low	High
A	Flour	-1	1
B	Butter	-1	1
C	Egg	-1	1

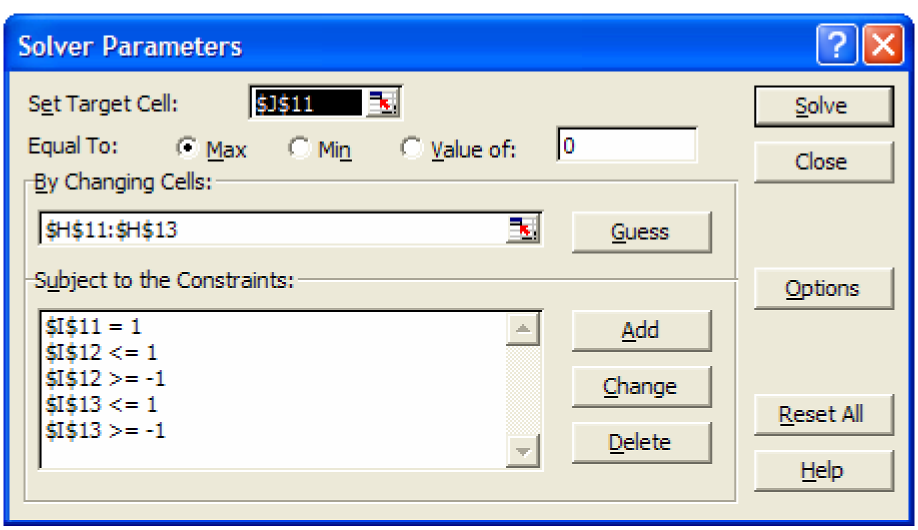
Predicted Output for Y:

Factor Name	Enter Actual Factor Setting - uncoded	Factor setting coded	Y-hat:	S-hat:
	1	1	4.865	0.91578
	0	0		
	0	0		

29. Click Tools > Add-Ins. Ensure that the Solver Add-in is checked. If the Solver Add-in does not appear in the Add-ins available list, you will need to re-install Excel to include all add-ins.



30. Click OK. Click Tools > Solver. Set the Solver Parameters as shown:



Cell J11 is the Y-hat, predicted average taste score. Solver will try to maximize this value. Cells H11 to H13 are the Actual Factor Settings to be changed. Cells I11 to I13 are the Coded Factor settings where the following constraints are given: I11=1; I12 >= -1; I12 <= 1; I13 >= -1; I13 <=1.

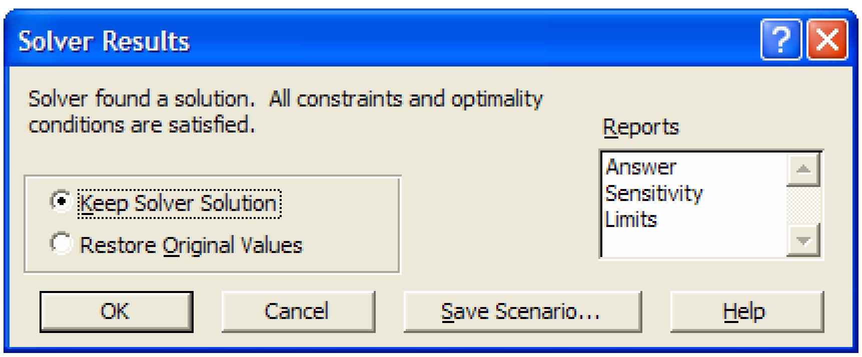
31. Click Solve. The solver results are given in the Predicted Output for Y as Butter = -1 and Egg = 1.

Factor	Factor Name	Low	High
A	Flour	-1	1
B	Butter	-1	1
C	Egg	-1	1

Predicted Output for Y:

Factor Name	Enter Actual Factor Setting - uncoded	Factor setting coded	Y-hat:	S-hat:
	1	1	5.9	0.68191
	-1	-1		
	1	1		

32. Solver indicates that a solution is found:



33. Click OK to keep the solution.

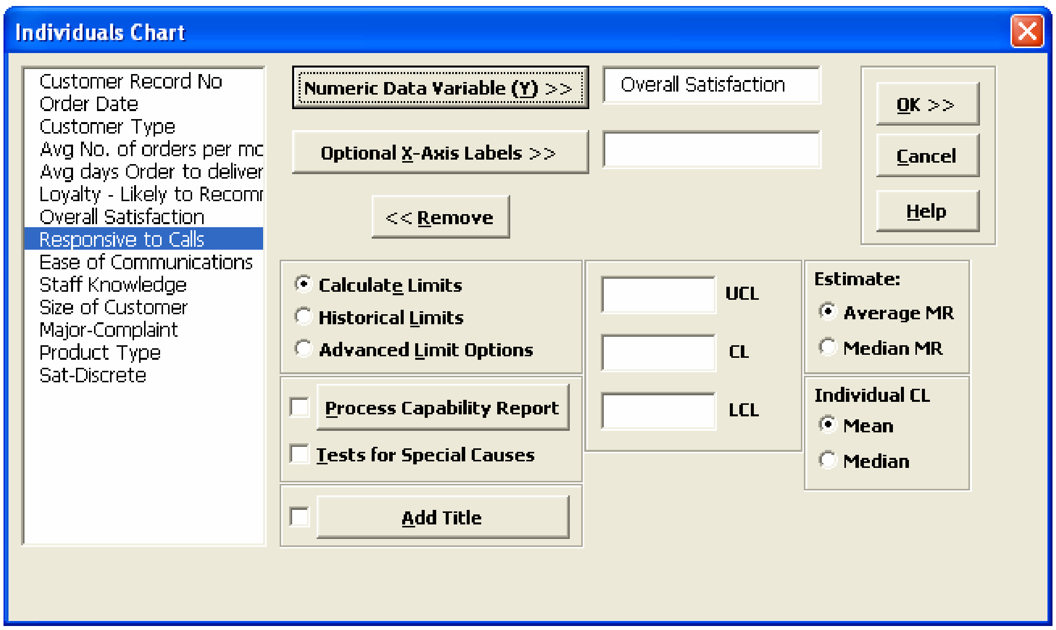
SigmaXL: Control Phase Tools: Statistical Process Control (SPC) Charts

Part A - Individuals Charts

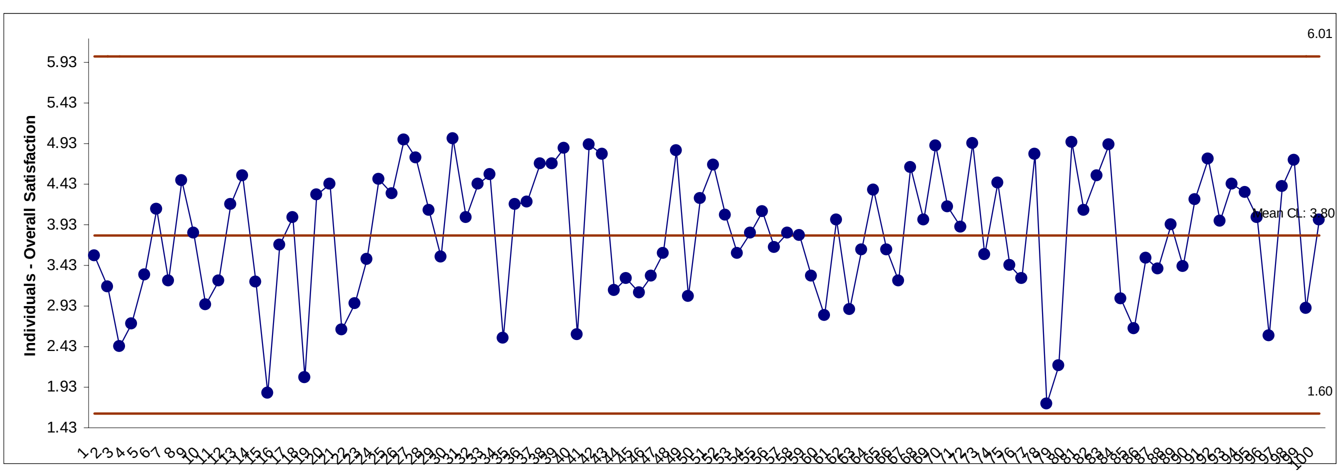
Individuals Charts

1. Open **Customer Data.xls**, click on Sheet 1. Click SigmaXL > Control Charts > Individuals. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

2. Select Overall Satisfaction as Y, ensure that Calculate Limits is selected.

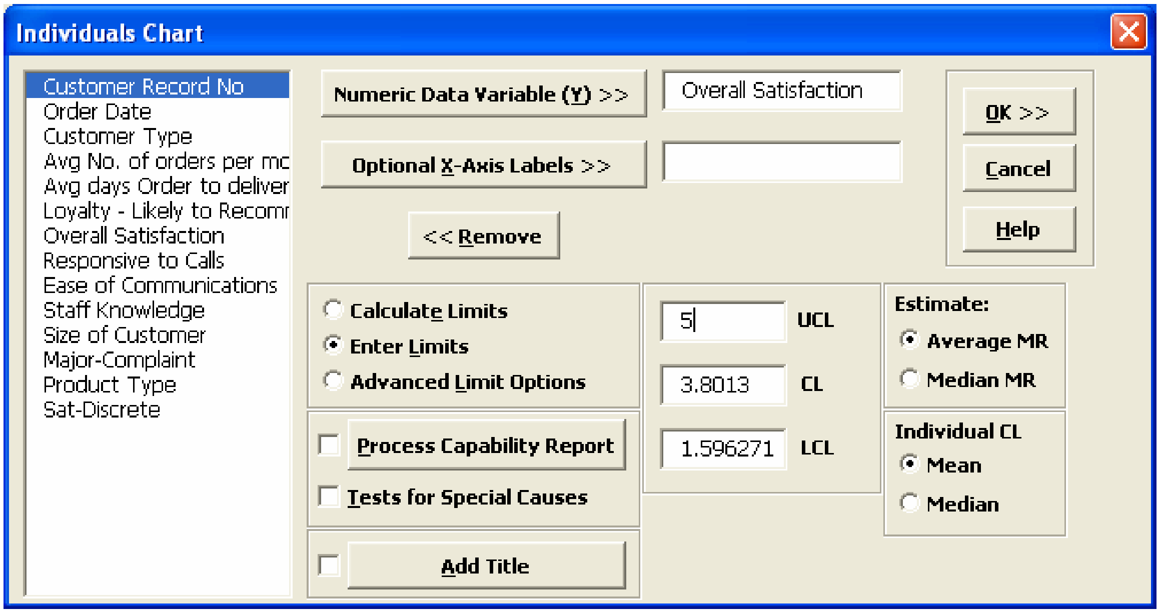


3. Click OK. Resulting Individuals control chart:

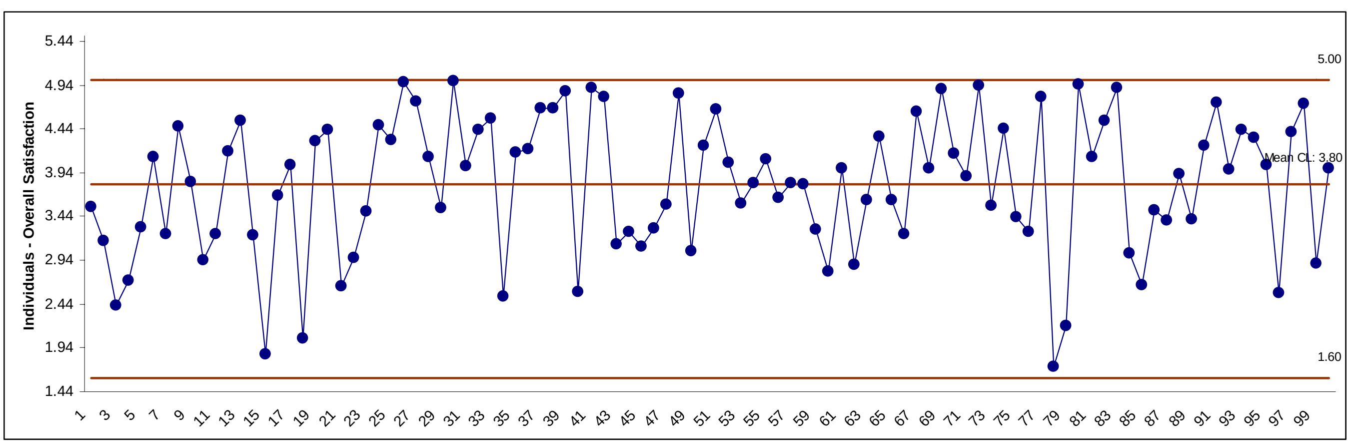


4. We have seen this data earlier as a run chart. The Control Chart adds calculated control limits. Note that the Upper Control Limit exceeds the survey upper limit of 5. Here it would be appropriate to change the UCL to 5.0. Click "Recall SigmaXL Dialog" menu or press **F3** to recall last dialog.

5. Select Overall Satisfaction as Y, select Historical Limits, change UCL to 5.



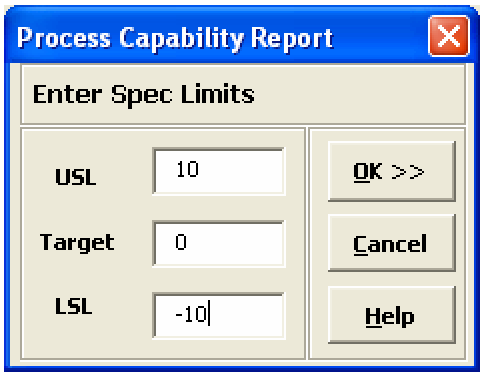
6. Click OK. Resulting Individuals chart with modified UCL:



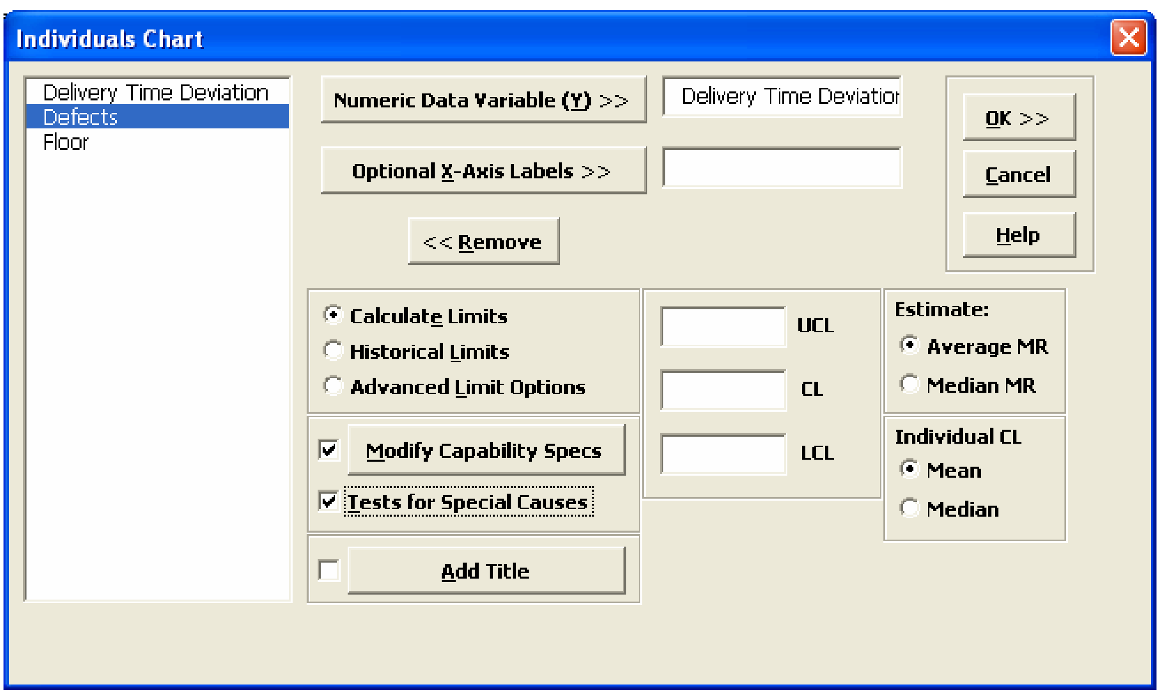
7. Open **Delivery Times.xls.** Click Sheet 1 Tab. This data set contains room service delivery time deviations in minutes. The Critical Customer Requirement is target time +/- 10 minutes.

8. Click SigmaXL > Control Charts > Individuals. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

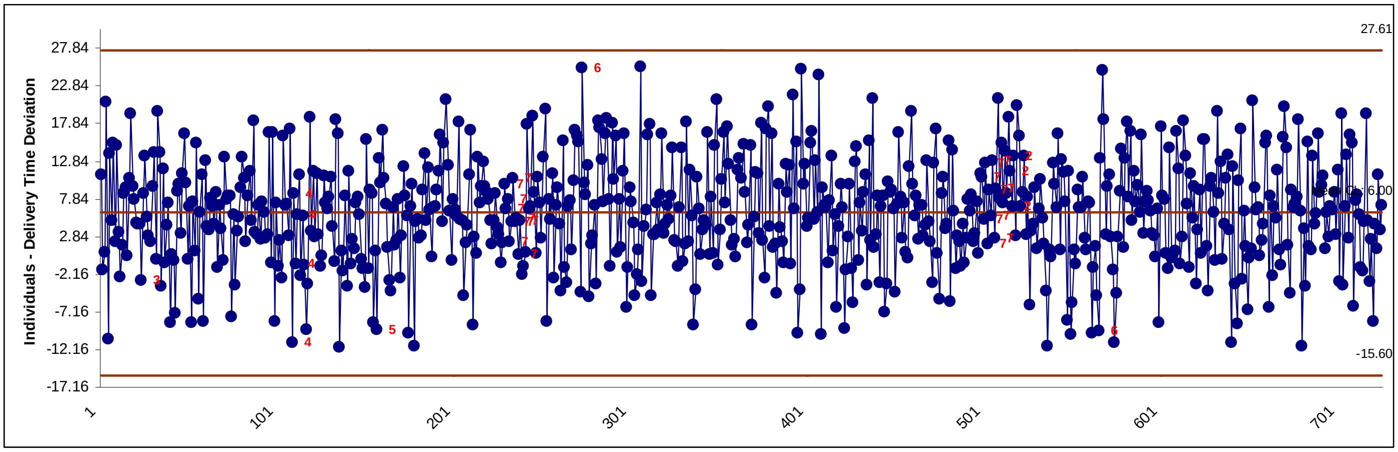
9. Select Delivery Time Deviation as Y, check Process Capability Report, specify USL = 10, Target = 0, LSL = -10



10. Click OK, check Tests for Special Causes, ensure that Calculate Limits is checked.



11. Click OK. Resulting chart:



Some tests for special causes are indicated on the chart. If more than one test fails, the number corresponds to the first failed test.

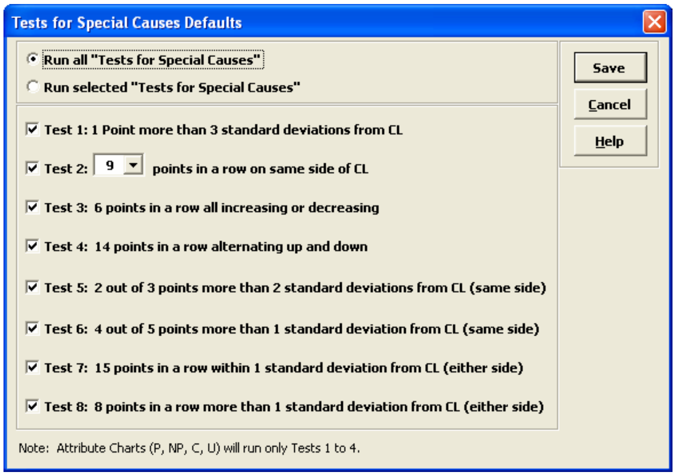
12. There are no points that exceed the +/- 3 sigma limits on this chart, but we see some indication of instability with tests for special causes. Clicking on the Indiv Tests Tab gives us a detailed report.:

Tests for Special Causes - Indiv - Delivery Time Deviation

Number of Data Points Failing Tests = 30

Observation No.	Test 1: 1 point more than 3 Stdev from CL	Test 2: 9 points in a row on same side of CL	Test 3: 6 points in a row all increasing or all decreasing	Test 4: 14 points in a row alternating up and down	Test 5: 2 out of 3 points more than 2 Stdev from CL (same side)	Test 6: 4 out of 5 points more than 1 Stdev from CL (same side)	Test 7: 15 points in a row within 1 Stdev from CL (either side)	Test 8: 8 points in a row more than 1 Stdev from CL (either side)
24			x					
109				x				
110				x				
111				x				
112				x				
157					x			
229							x	
230							x	
231							x	
232							x	
233							x	
234							x	
235							x	
236							x	
237							x	
238							x	
273						x		
499							x	
500							x	
501							x	
502							x	
503							x	
504							x	
505							x	
506							x	
507							x	
515		x						
516		x						
517		x						
565						x		

13. These tests for special causes can have defaults set to apply any or all of Tests 1-8. Test 2 can be set to 7, 8, or 9 points in a row on same side of CL. Click SigmaXL > Control Charts > "Tests for Special Causes" Defaults to run selected tests for special causes:



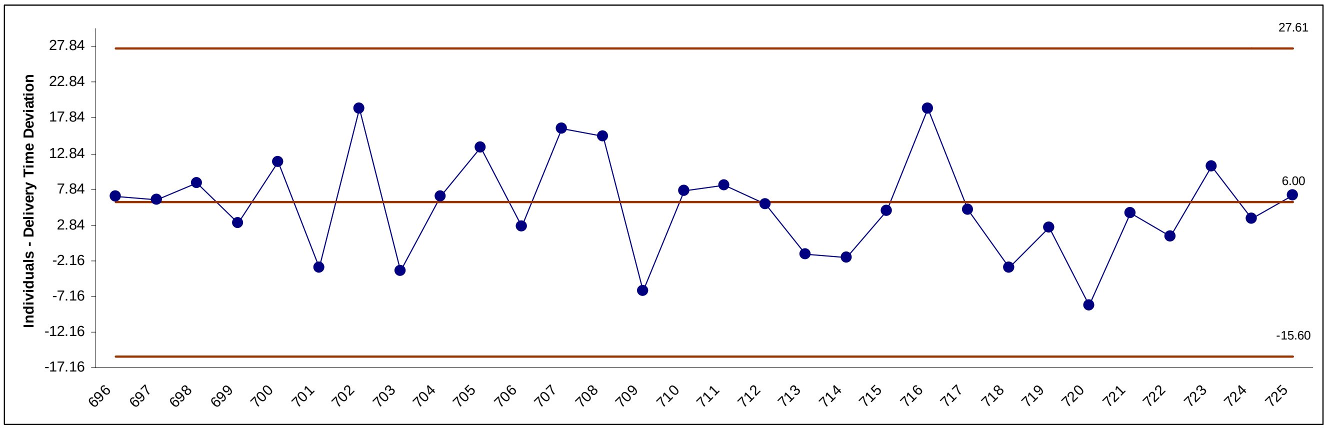
Note that these defaults will apply to Individuals and X-bar charts. Test 1 to 4 settings will be applied to Attribute Charts.

14. Click on Indiv Proc Cap Tab to view the Process Capability Report, which includes potential (short term) capability indices Cp and Cpk:

Report: Indiv - Delivery Time Deviation	
Count =	725
Mean =	6.0036
StDev (Overall, Long Term) =	7.1616
StDev (Within, Short Term) =	7.2020
USL =	10
Target =	0
LSL =	-10
Capability Indices using Overall StDev	
Pp =	0.47
Ppu =	0.19
Ppl =	0.74
Ppk =	0.19
Cpm =	0.36
Potential Capability Indices using Within StDev	
Cp =	0.46
Cpu =	0.18
Cpl =	0.74
Cpk =	0.18
Expected Overall Performance	
ppm > USL =	288409
ppm < LSL =	12720
ppm Total =	301130
% > USL =	28.84%
% < LSL =	1.27%
% Total =	30.11%
Actual (Empirical) Performance	
% > USL =	26.90%
% < LSL =	1.38%
% Total =	28.28%

15. While this process demonstrated some slight instability on the control charts, the bigger issue was being late 6 minutes on average and having a Standard Deviation of 7.2 minutes! One improvement implemented was rescheduling the service elevators so that Room Service and Maintenance were not both trying to use them during peak times.

16. Click on the Indiv sheet. With 725 data points, you may want to have a closer look at the most recent data. To do this, click SigmaXL Chart Tools > Show Last 30 Points. (If this menu item does not appear, click on any cell adjacent to the chart). The resulting chart is shown:



17. To reset the chart, click SigmaXL Chart Tools > Show All Data Points.

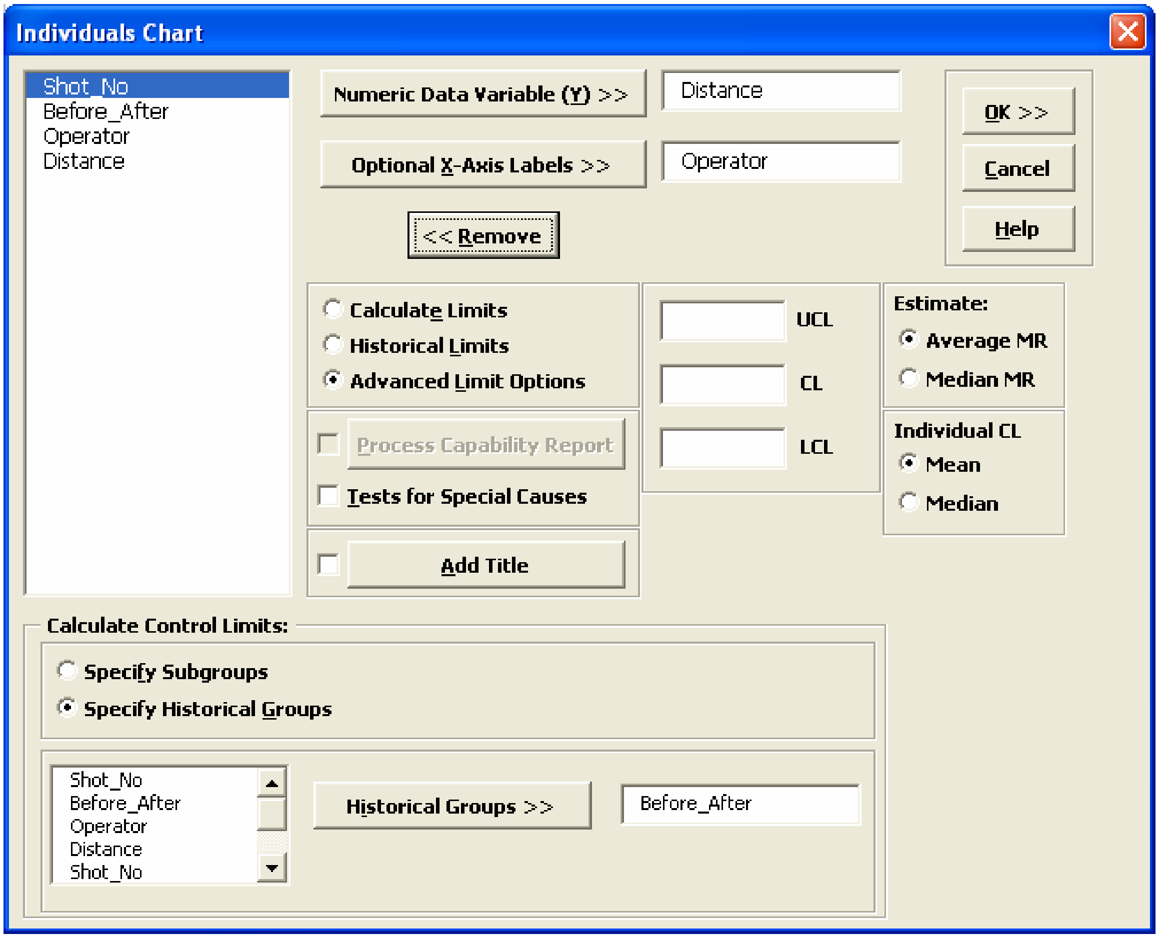
Individuals Charts: Advanced Limit Options – Historical Groups

1. Open **Catapult Data Before After Improvement.xls.** Click Sheet 1 Tab. This data set contains Catapult firing distances. Before_After denotes before improvement and after improvement. The target distance is 100 inches with the goal being to hit the target and minimize variation about the target. We would like to use an individuals control chart with historical groups to split the limits demonstrating the before versus after improvement.

2. Click SigmaXL > Control Charts > Individuals. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

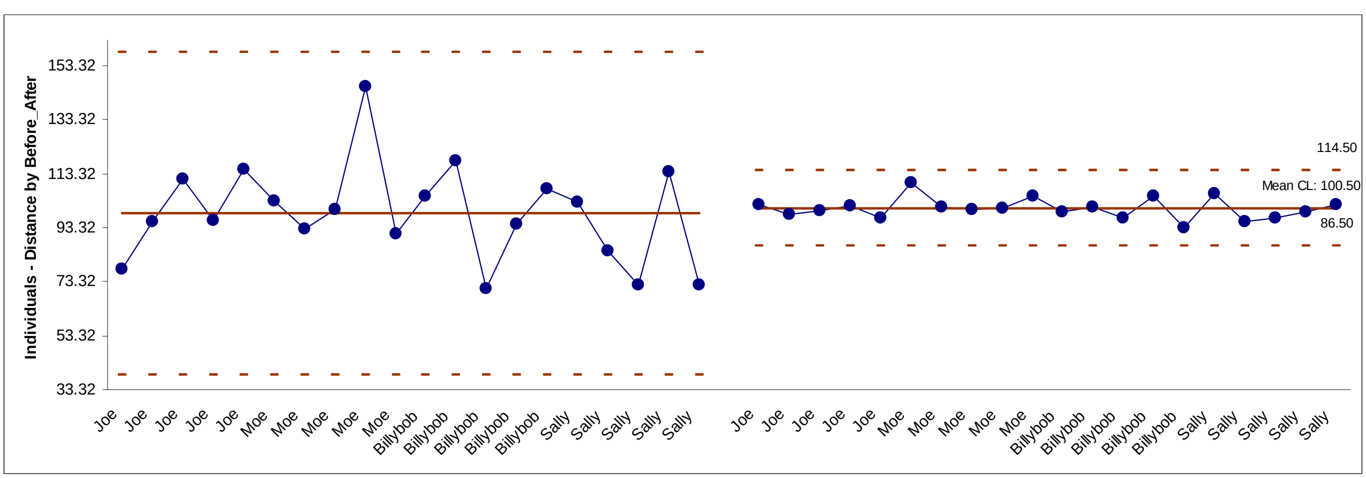
3. Select Distance as the Numeric Data Variable (Y). Select Operator for Optional X-Axis Labels.

4. Click Advanced Limit Options. Select Specify Historical Groups. Select Before_After for Historical Groups.



Note: Process Capability analysis is not permitted when Historical Groups are used.

5. Click OK. The resulting Individuals Control Chart with split limits based on historical groups is shown, demonstrating a clear process improvement:



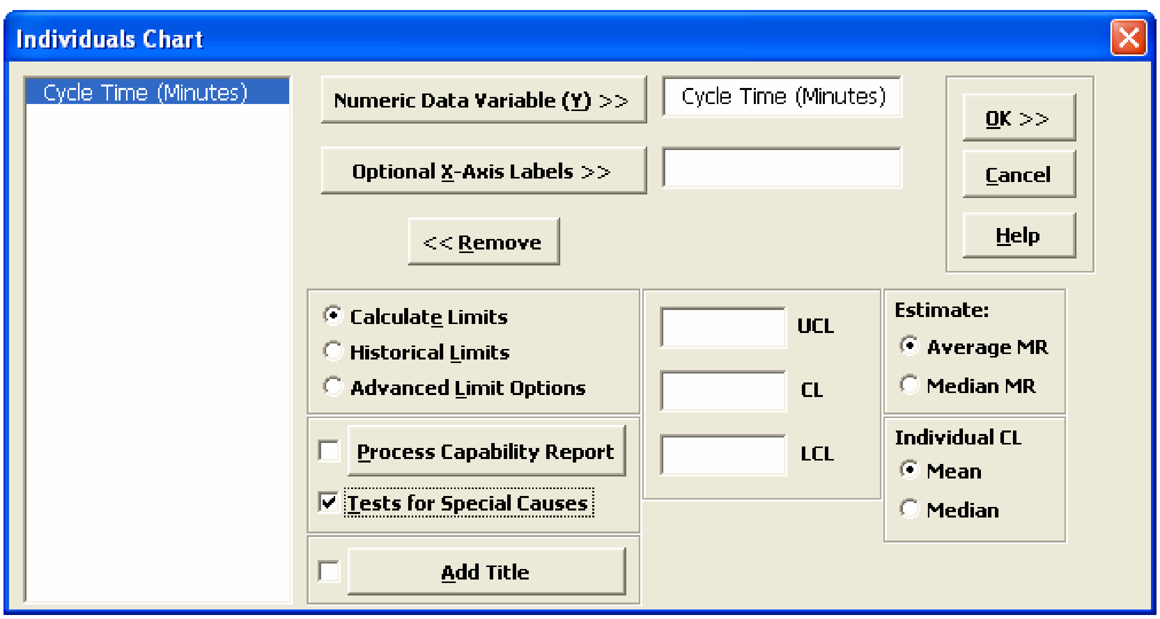
Individuals Charts for Non-Normal Data (Box-Cox Transformation)

An important assumption for Individuals Charts is that the data be normally distributed (unlike the X-Bar Chart which is robust to non-normality due to the central limit theorem). If the data is non-normal, the Box-Cox Transformation tool can be used to convert non-normal data to normal by applying a power transformation.

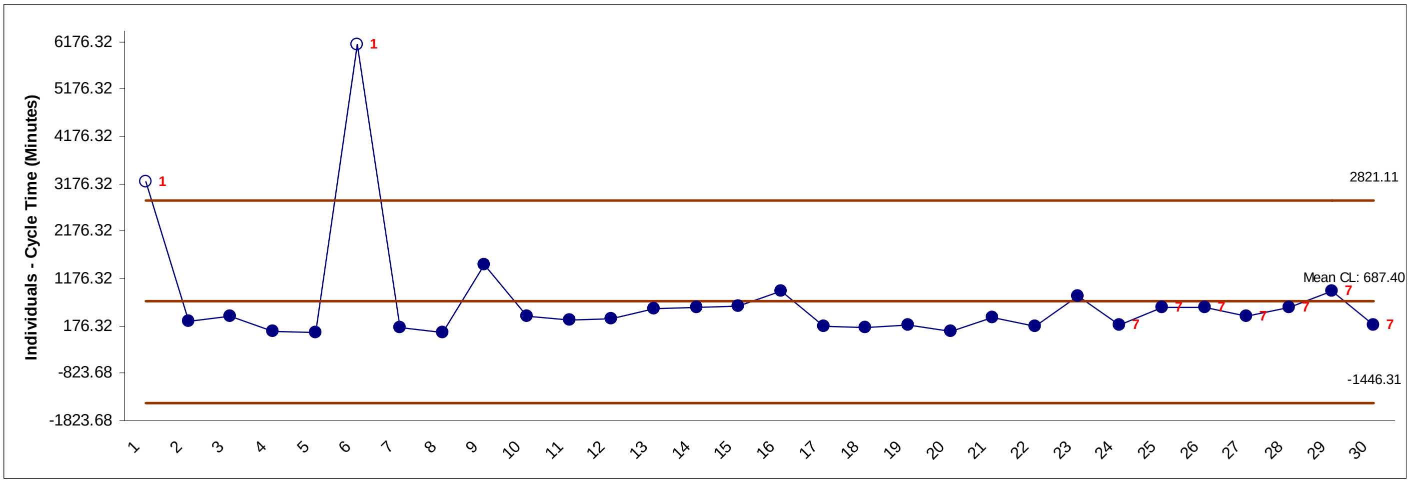
1. Open the file **Non-Normal Cycle Time.xls**. This contains continuous non-normal data of process cycle times. We performed a Process Capability study with this data earlier in the Measure Phase, Part H.

2. Initially we will ignore the non-normality in the data and construct an Individuals Chart. Click SigmaXL > Control Charts > Individuals. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

3. Select Cycle Time (Minutes) as the Numeric Data Variable (Y). Select Calculate Limits. Check Tests for Special Causes.



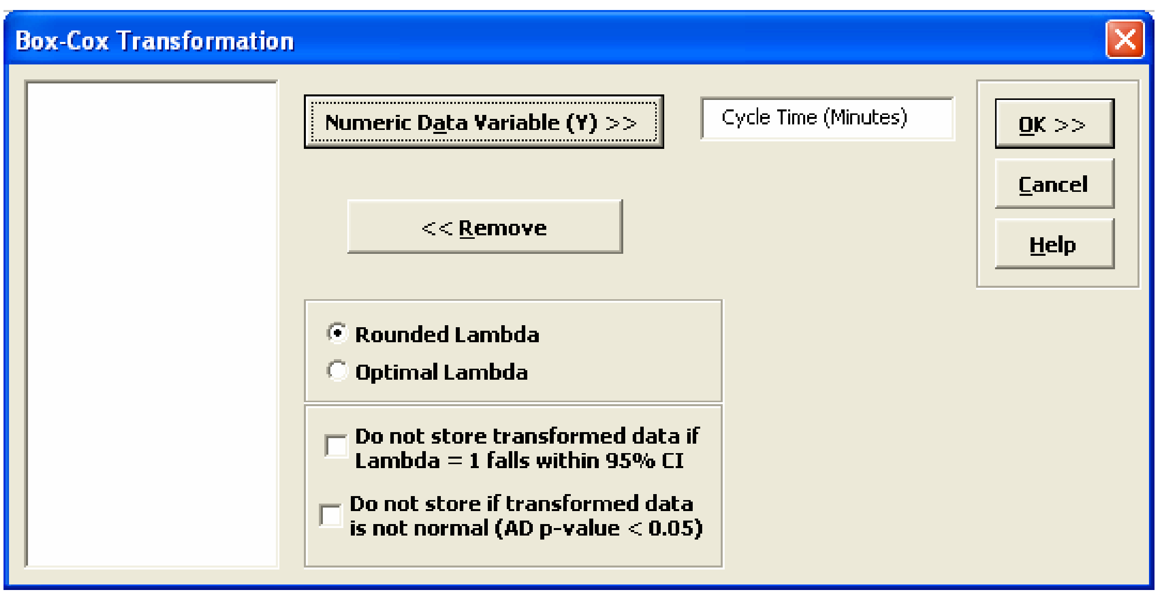
4. The resulting Individuals Chart is shown:



5. This chart clearly shows that the process is "out-of-control". But is it really? Non-normality can cause serious errors in the calculation of individual chart control limits triggering false alarms (Type I errors) or misses (Type II errors).

6. Select Sheet 1 (or press **F4**). Click SigmaXL > Control Charts > Box-Cox Transformation. Ensure that entire data table is selected. If not, check "Use Entire Data Table". Click Next.

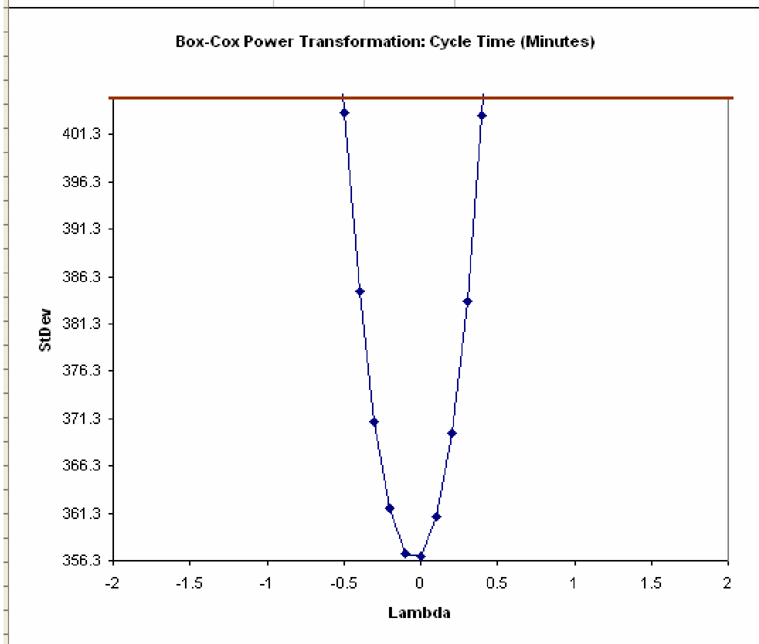
7. Select Cycle Time (Minutes) as the Numeric Data Variable (Y)



8. Click OK. The resulting Box-Cox Transformation report is shown:

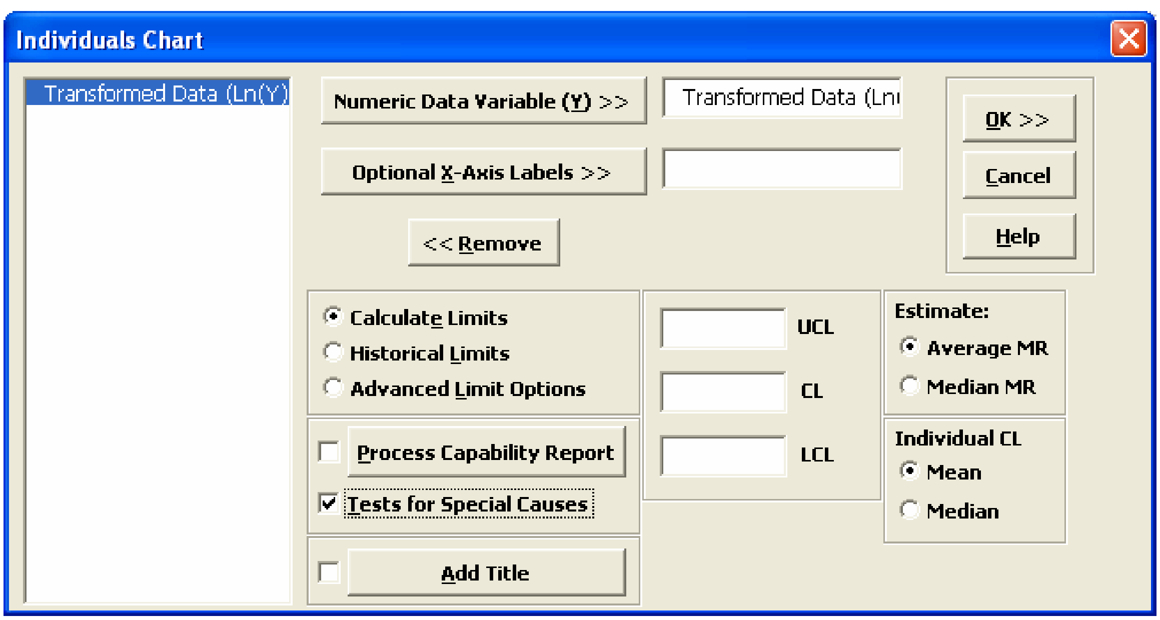
Box-Cox Power Transformation: Cycle Time (Minutes)

Optimal Lambda	-0.04
Final Lambda	0
UC Lambda (95%)	0.407756
LC Lamda (95%)	-0.506879
Anderson Darling Normality Test for Transformed Data:	
A-Squared	0.326821
AD P-value	0.5063

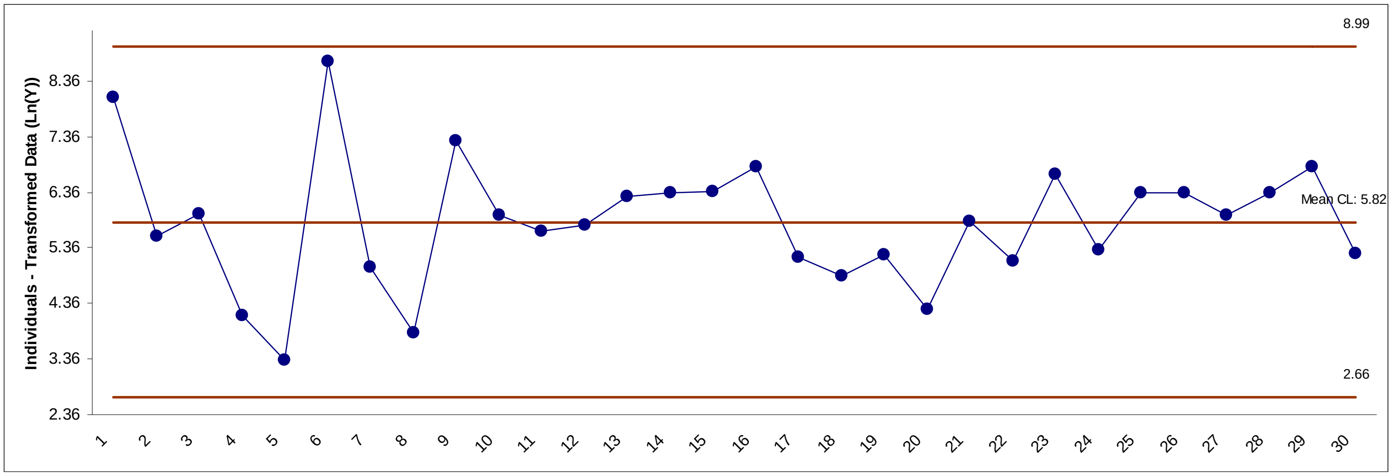


Cycle Time (Minutes)	Transformed Data (Ln(Y))
3216	8.07589363
261	5.564520407
392	5.97126184
63	4.143134726
28	3.33220451
6101	8.716207971
151	5.017279837
46	3.828641396
1465	7.289610521
383	5.948034989
287	5.659482216
322	5.774551546
538	6.28785856
574	6.352629396
586	6.37331979
920	6.82437367
178	5.18178355
129	4.859812404
187	5.231108617
71	4.262679877
342	5.834810737
167	5.117993812
794	6.677083461
205	5.323009979
576	6.356107661
575	6.354370041
381	5.942799375
576	6.356107661
918	6.822197391
190	5.247024072

9. Select cells G1:G31. Click SigmaXL > Control Charts > Individuals. Click Next. Select Transformed Data (Ln(Y)) as the Numeric Data Variable (Y). Check Tests for Special Causes.



10. Click OK. The resulting individuals chart is shown:



11. Compensating for the non-normality, we see that this is in fact a stable process. One disadvantage of this chart is that the transformed Ln(Y) data is not easy to understand and interpret. One option is to apply the inverse transformation (=EXP(UCL), =EXP(CL), =EXP(LCL)) to the Control Limits above and plot the raw data with the modified limits. This allows us to display the original data but has the disadvantage that the Tests for Special Causes report cannot be used. Note, if the lambda power transformation is anything other than 0 (Ln), then use the following formulas to determine the modified Control Limits:
=UCL^(1/Lambda)
=CL^(1/Lambda)
=LCL^(1/Lambda).
If Lambda is negative, UCL and LCL will be reversed.

Part B - X-Bar & Range Charts

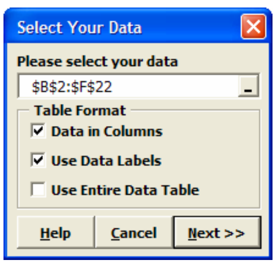
X-Bar & R Charts

1. Open the file **Catapult Data – Xbar Control Charts.xls**. Each operator fires the ball 3 times. The target distance is 100 inches. The Upper Specification Limit (USL) is 108 inches. The Lower Specification Limit (LSL) is 92 inches.

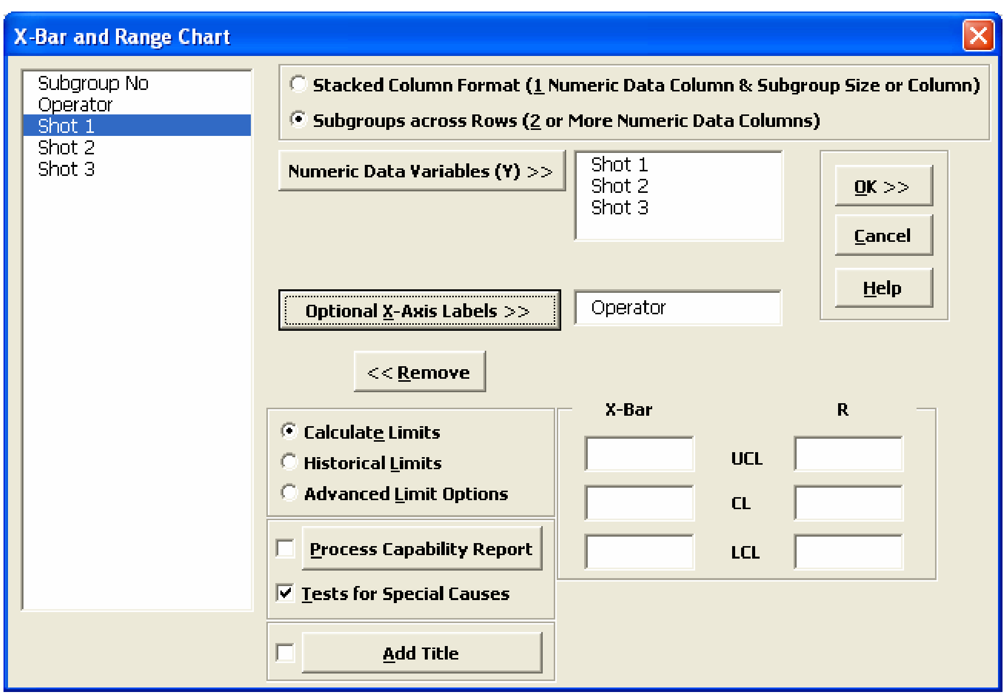
2. Select B2:F22, here we will only use the first 20 subgroups to determine the control limits.

3. Select SigmaXL > Control Charts > X-Bar & R.

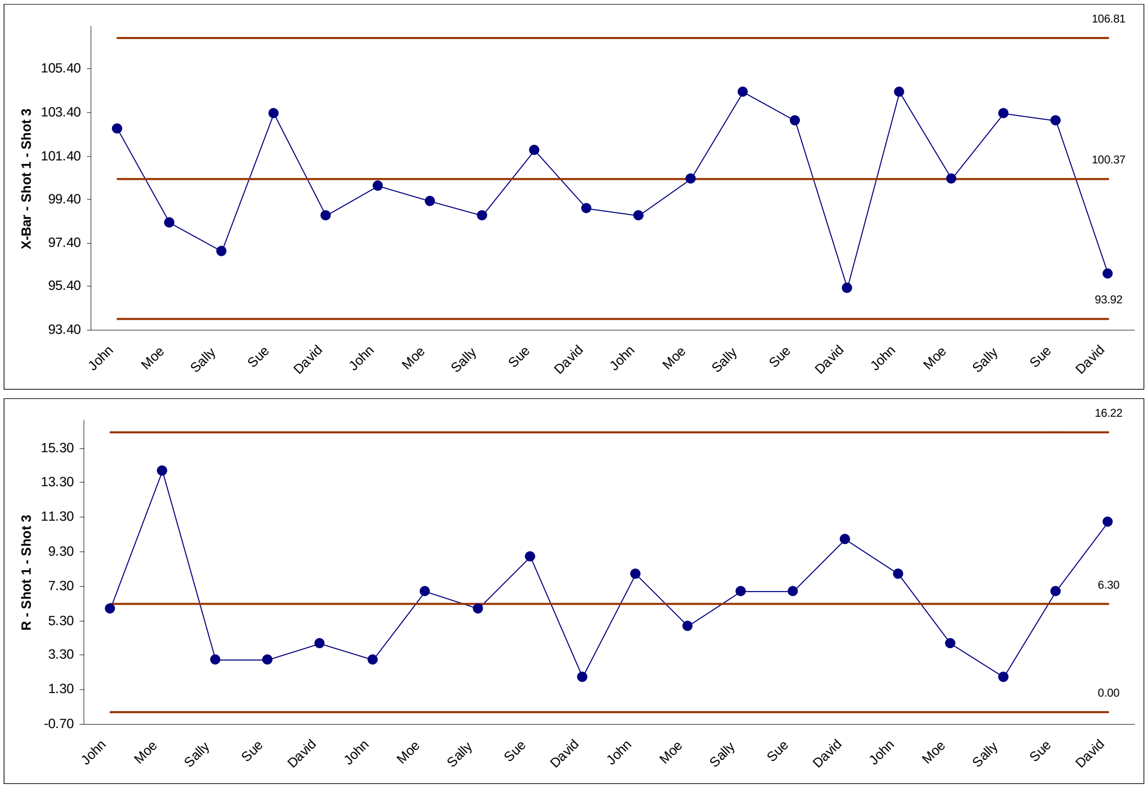
4. Do not check Use Entire Data Table!



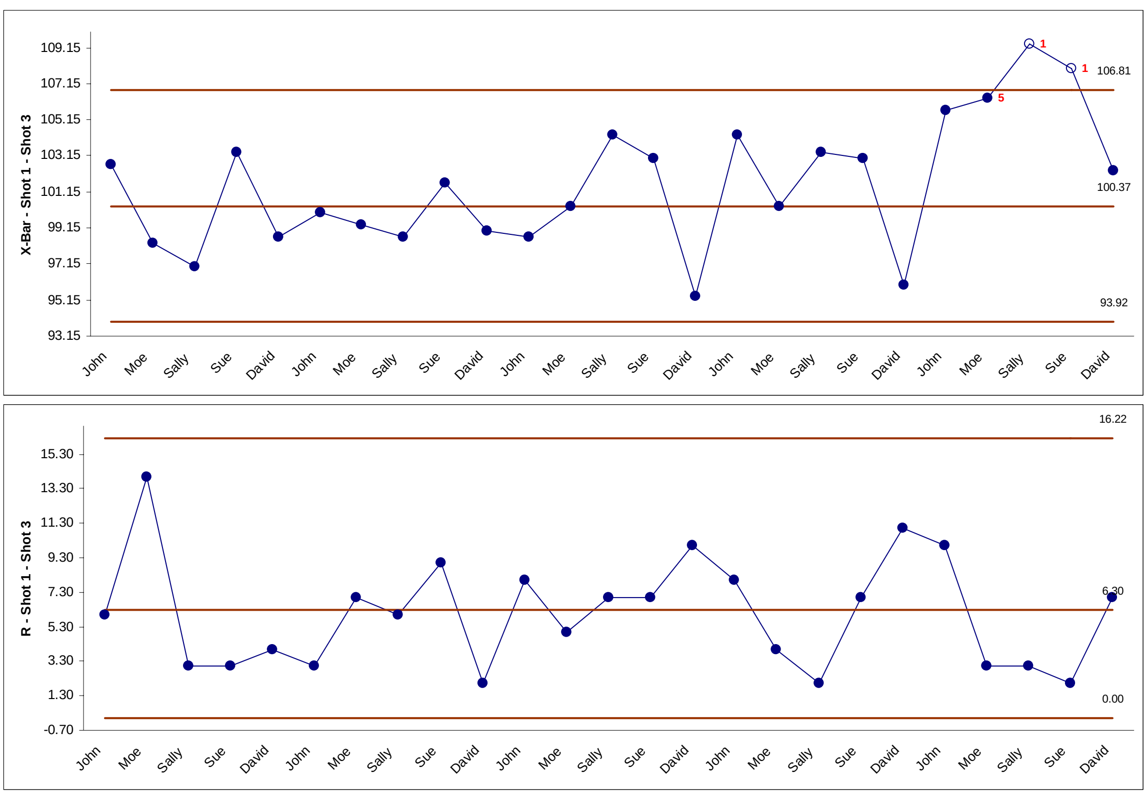
5. Click Next. Select Subgroups across Rows, select Shot 1, Shot 2, Shot 3 as the Numeric Data Variables (Y). Select Operator as Optional X-axis labels. Check Tests for Special Causes as shown:



6. Click OK. Resulting X-bar & R charts:



7. This is currently a stable catapult process. Subgroups 21 to 25 were added afterwards. To add the "new" data to this chart, click SigmaXL Chart Tools > Add Data as shown:



8. Note that the Add Data button does NOT recalculate the control limits. Once control limits are established, they should only be recalculated when a deliberate process change or improvement is introduced. (Control Limits can be recalculated using SigmaXL Chart Tools > Recalculate Control Limits, but a warning message "Are you sure that you want to recalculate control limits?" is given).

9. The "Tests for Special Causes" report gives us more detail on the recent instability:

Tests for Special Causes - X-Bar - Shot 1 - Shot 3
Number of Data Points Failing Tests = 3

Observation No.	Test 1: 1 point more than 3 Stdev from CL	Test 2: 9 points in a row on same side of CL	Test 3: 6 points in a row all increasing or all decreasing	Test 4: 14 points in a row alternating up and down	Test 5: 2 out of 3 points more than 2 Stdev from CL (same side)	Test 6: 4 out of 5 points more than 1 Stdev from CL (same side)	Test 7: 15 points in a row within 1 Stdev from CL (either side)	Test 8: 8 points in a row more than 1 Stdev from CL (either side)
22					x	x		
23	x				x	x		
24	x				x	x		

The X-bar chart and "Tests for Special Causes" report clearly shows that process is now out of control with an unstable mean. The process must be stopped, and the Out-of-Control Action Plan must be followed to determine and fix the root cause. In this case, the assignable cause was a change of rubber band requiring a reset of the pull back angle. The use of tests for special causes gave us an early warning of this at observation number 22.

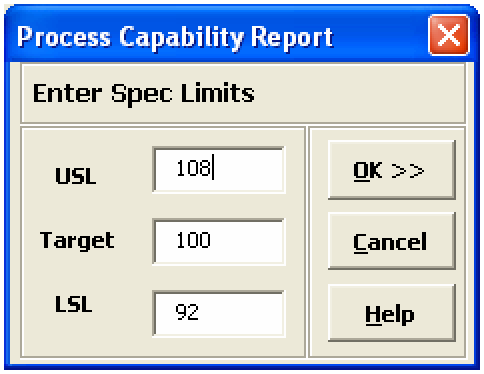
Note that the Range chart is in-control even though the X-Bar chart is out-of-control.

10. The tests for special causes can have defaults set to apply any or all of Tests 1-8. Test 2 can be set to 7, 8, or 9 points in a row on same side of CL. Click SigmaXL > Control Charts > "Tests for Special Causes" Defaults to run selected tests for special causes. (Note that these defaults will apply to Individuals and X-bar charts. Test 1 to 4 settings will be applied to Attribute Charts).

11. Now we will look at Process Capability Indices for this process. Click on Sheet 1 (or press **F4** to activate last worksheet). Click SigmaXL > Control Charts > X-Bar & R. Check "Use Entire Data Table". Click Next. (Alternatively select B2:F27, press **F3**).

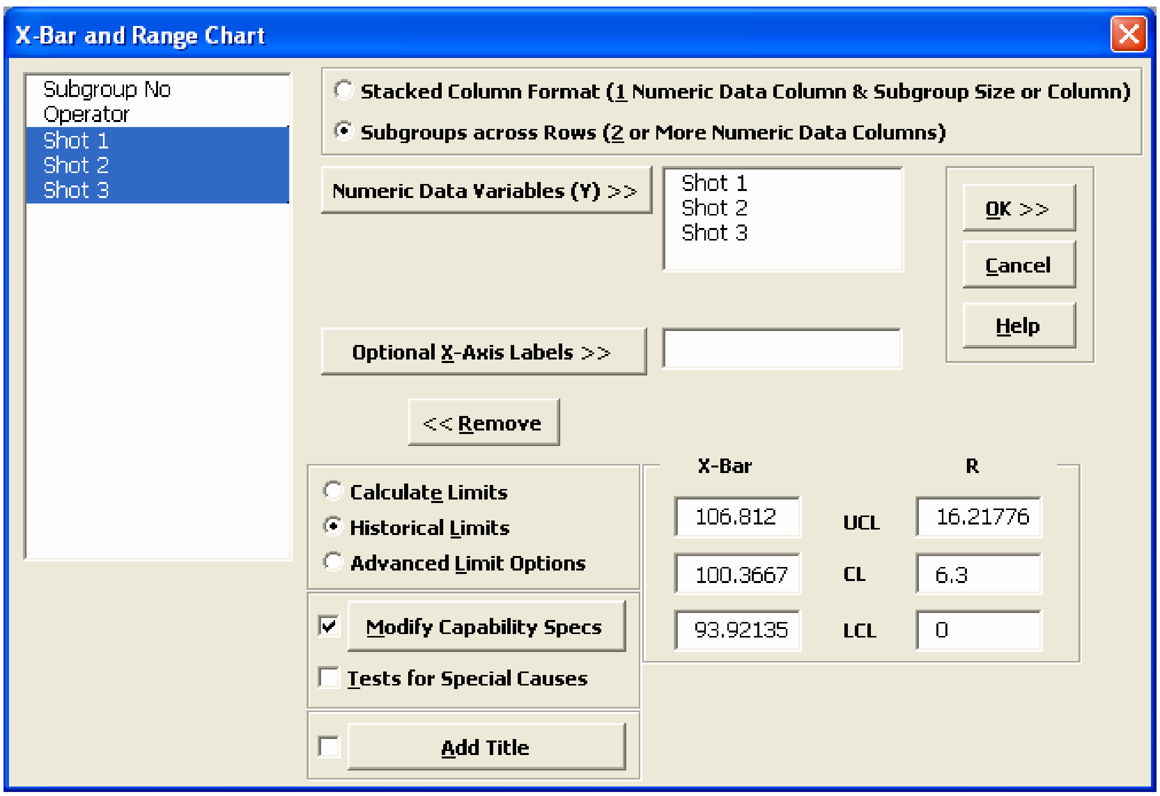
12. Select Shots 1-3 as Numeric Data Variables (Y). Select Historical Limits. These are the limits calculated with the original 20 subgroups.

13. Check Process Capability Report. Enter USL = 108, Target = 100, LSL = 92.



14. Click OK.

15. The resulting dialog box settings are shown:



16. Click OK. Click X-Bar & R – Proc Cap sheet for the Process Capability report:

Report: X-Bar & R - Shot 1 - Shot 3	
Count =	75
Mean =	101.56
StDev (Overall, Long Term) =	4.6156
StDev (Within, Short Term) =	3.5676
USL =	108
Target =	100
LSL =	92
Capability Indices using Overall StDev	
Pp =	0.58
Ppu =	0.47
Ppl =	0.69
Ppk =	0.47
Cpm =	0.55
Potential Capability Indices using Within StDev	
Cp =	0.75
Cpu =	0.60
Cpl =	0.89
Cpk =	0.60
Expected Overall Performance	
ppm > USL =	81468
ppm < LSL =	19168
ppm Total =	100636
% > USL =	8.15%
% < LSL =	1.92%
% Total =	10.06%
Actual (Empirical) Performance	
% > USL =	5.33%
% < LSL =	4.00%
% Total =	9.33%

Note the difference between Pp and Cp; Ppk and Cpk. This is due to the process instability. If the process was stable, the actual performance indices Pp and Ppk would be closer to the Cp and Cpk values.

Tip: Another approach here could have been to select Advanced Limit Options and specify Subgroup Numbers 1 to 20 for calculation of the control limits.

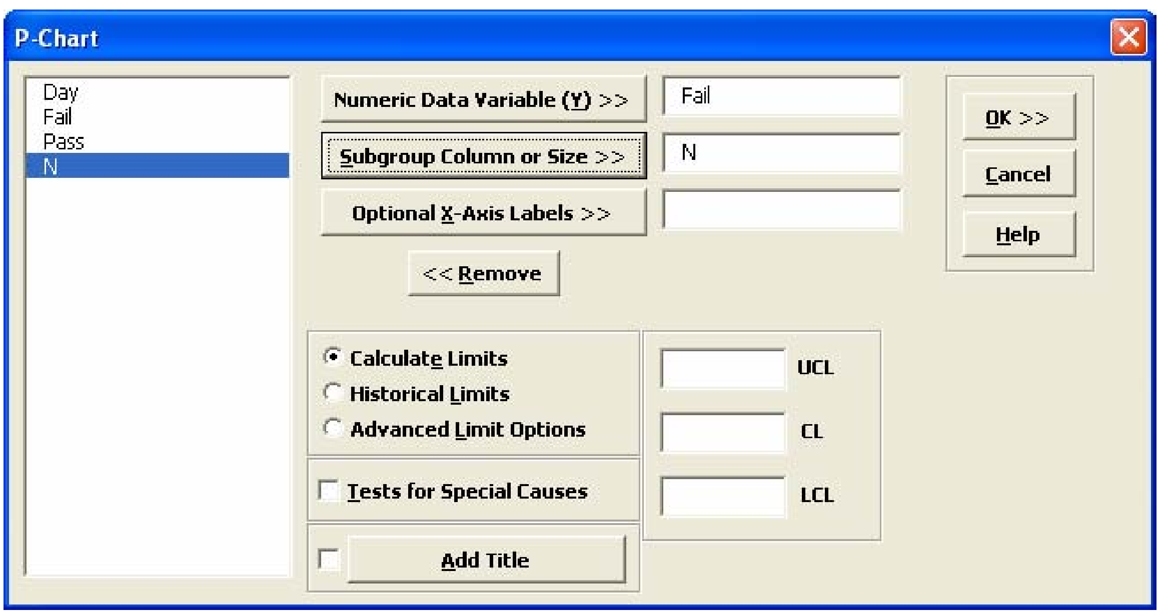
Part C - P-Charts

P-Charts

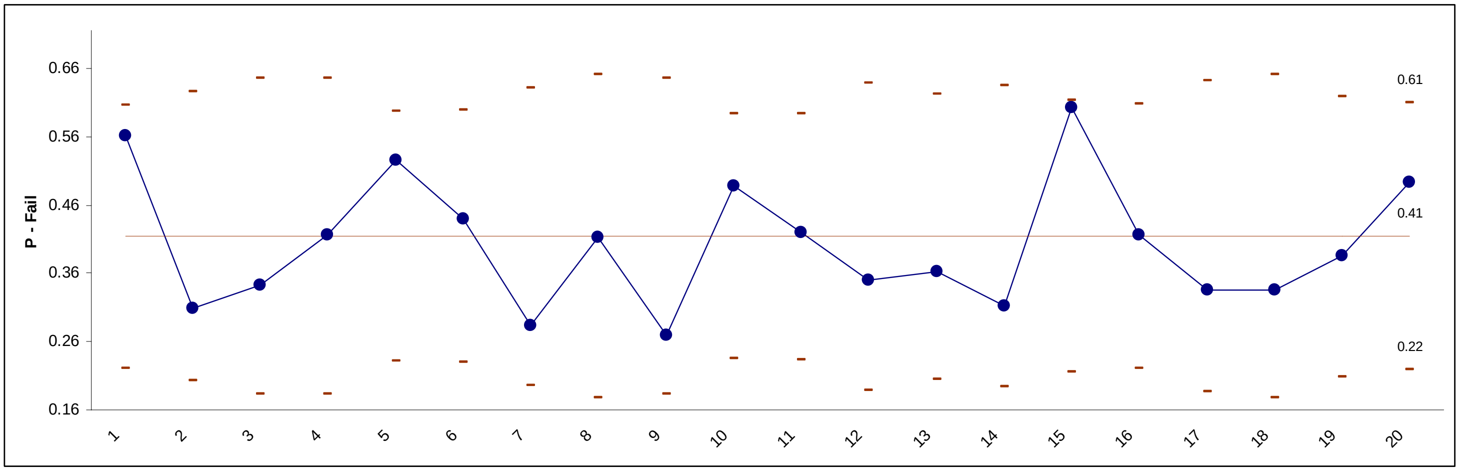
1. Open **New York Daily Cycle Time – Discrete.xls**. This is data from the Sigma Savings and Loans company, New York location. Each day the cycle time (in days) for completed loans and leases were recorded. N indicates the number of loans counted. A "Fail" was recorded if the cycle time exceeded the critical customer requirement of 8 days. Note that we are not recommending that continuous data be converted to discrete data in this manner, but using this data to illustrate the use of P charts for Discrete or Attribute data.

2. Select SigmaXL > Control Charts > P. Ensure that B3:E23 are selected, click Next.

3. Select "Fail" as the Numeric Data Variable (Y), "N" as the Subgroup Column (Size). If we had a fixed subgroup size the numerical value of the subgroup size could be entered instead of Column N.



4. Click OK. Resulting P-Chart:



The moving limits are due to the varying sample sizes. While this P-chart shows stability, a much bigger concern is the average 41% failure rate to deliver the loans/leases in 8 days or less!

Part D – Advanced Charts: I-MR-R/S

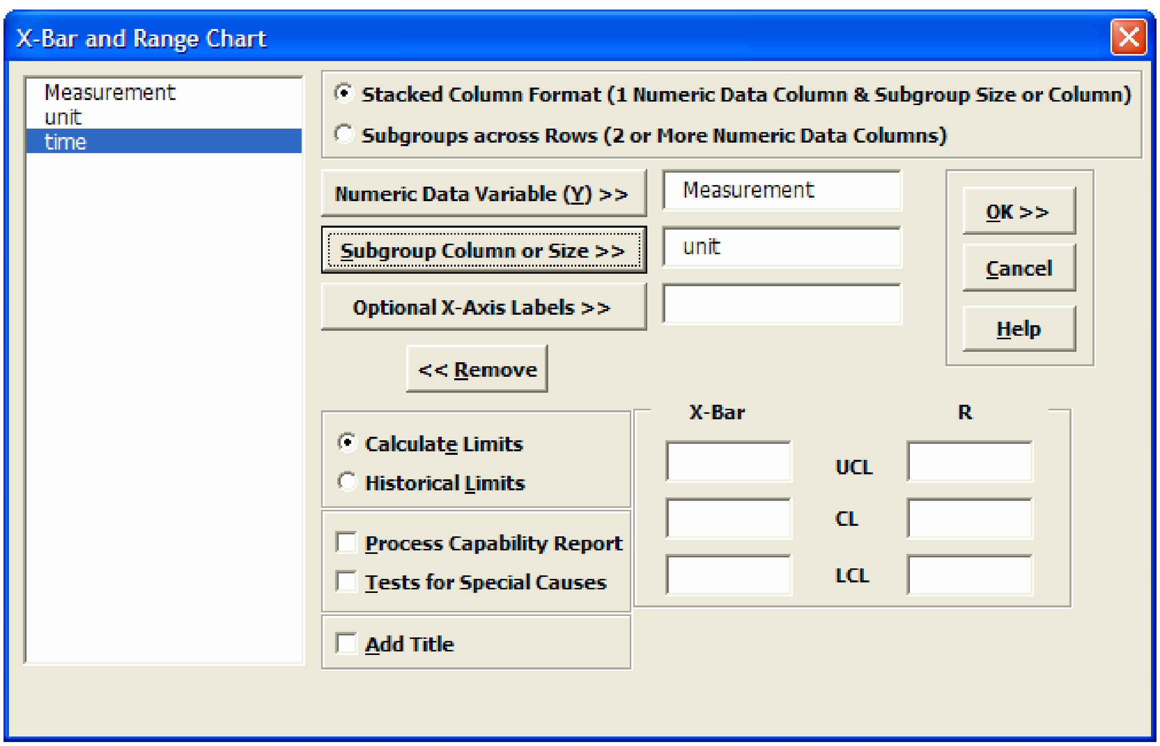
I-MR-R Charts

If the within-subgroup variability is much smaller than between subgroup, the classical X-bar & R (or S) chart will not work, producing numerous (false) alarms. The correct chart to use, in this case, is the I-MR-R (or S) chart. The subgroup averages are treated as individual values (I-MR) and the within subgroup ranges are plotted on the Range chart.

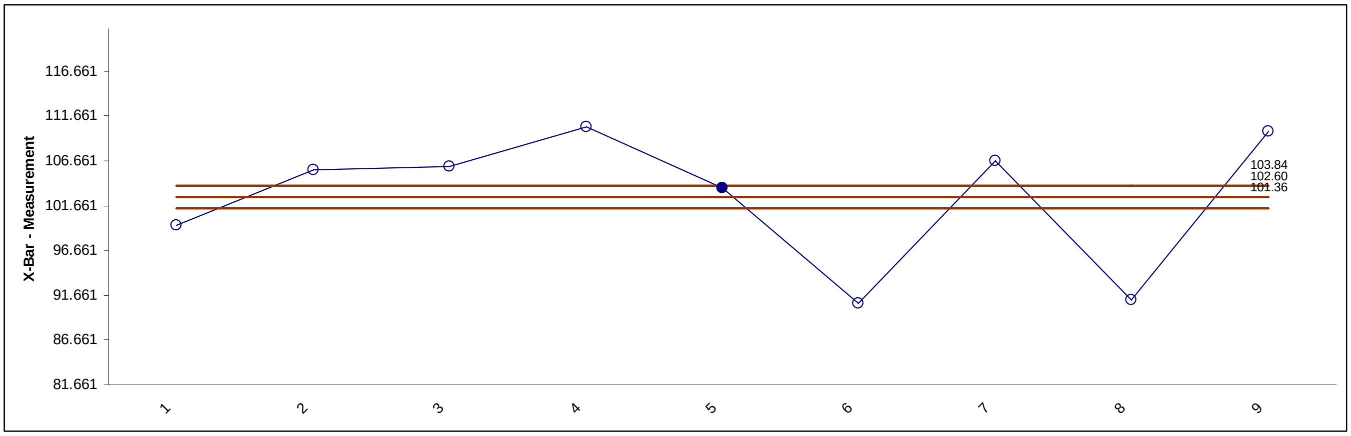
1. Open **Between.xls.** We saw this data previously using Multi-Vari charts. First we will incorrectly use the X-bar & R chart, and then apply the correct I-MR-R chart.

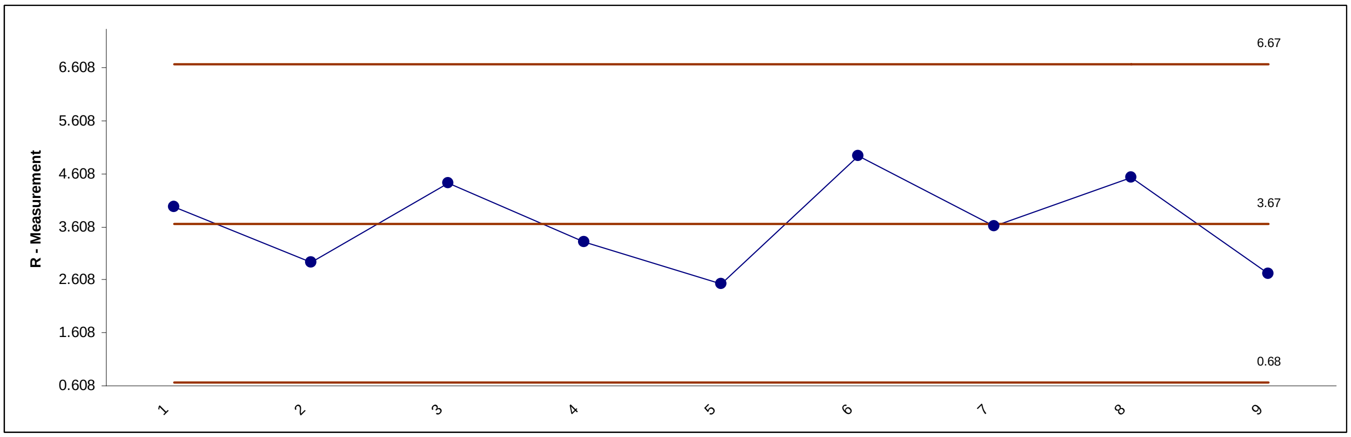
2. Click SigmaXL > Control Charts > X-bar & R. Check Use Entire Data Table.

3. Click Next. Select Stacked Column Format. Select Measurement as Y; select unit as Subgroup Column.



4. Click OK. Resulting X-bar & R chart:

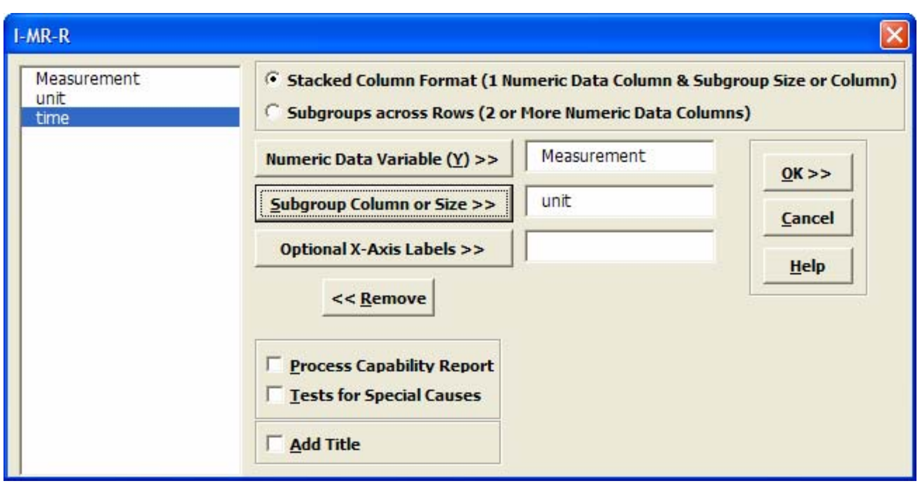




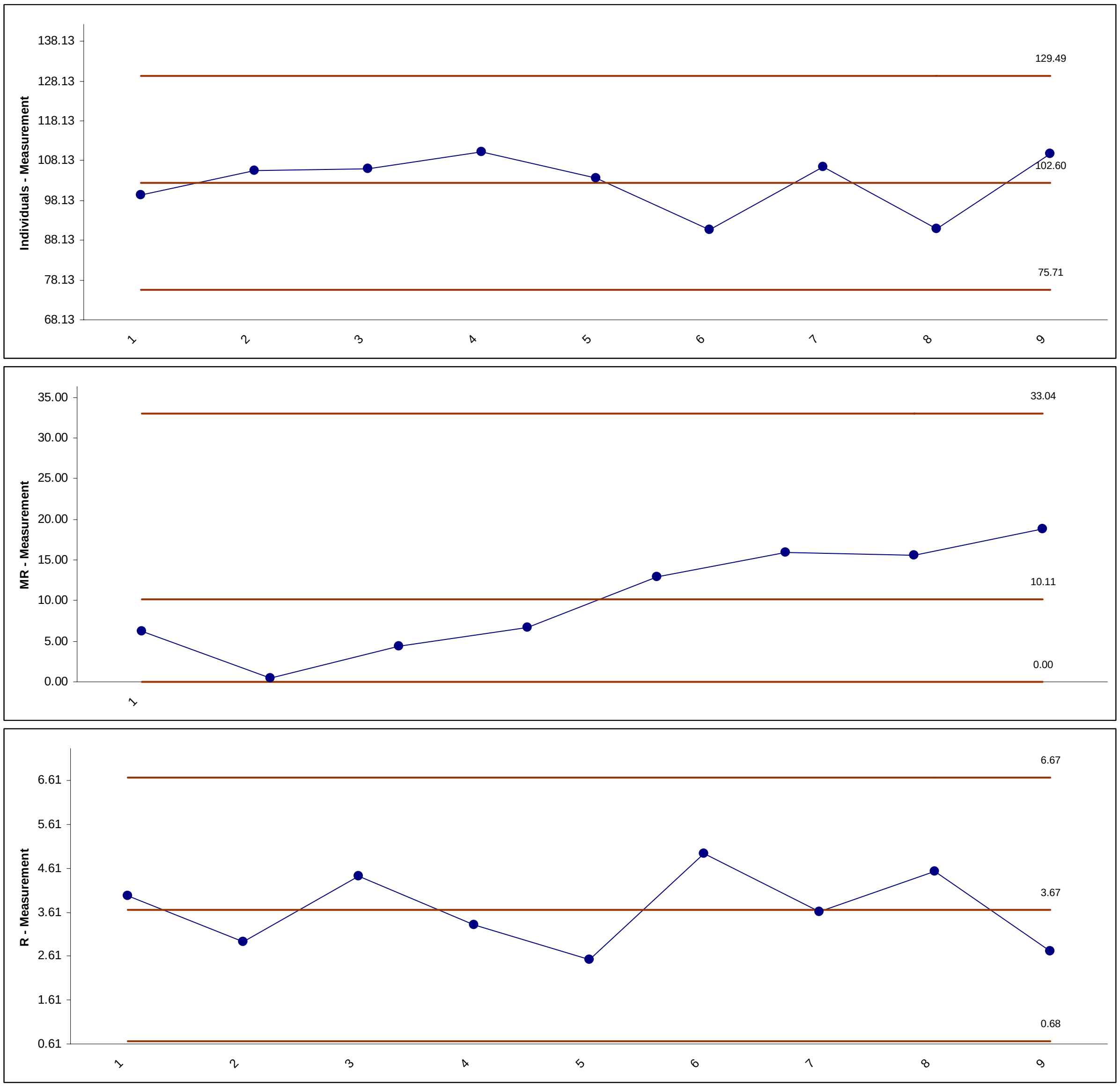
5. Almost all of the data points in the X-bar chart are out-of-control! This is due to the small within-subgroup variability (the control limits are calculated from the within-subgroup variability).

6. Click Sheet 1. Select SigmaXL > Control Charts > Advanced Charts > I-MR-R.

7. Click Next. Select Stacked Column Format. Select Measurement as Y; select unit as Subgroup Column.



8. Click OK. Resulting I-MR-R chart:



This chart is much cleaner, showing a stable Individuals and Range chart. The MR chart may be trending up, but we would want to collect more data before making this conclusion. Typically you want at least 20 (30 preferred) subgroups before calculating final control limits.

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